CRANFIELD UNIVERSITY

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The use of visual analytics in decision making in operations and supply chain management: A Systematic Literature Review

SCHOOL OF MANAGEMENT
MRes in Management Research

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This thesis is submitted in partial fulfilment of the requirements for the degree of Master of Research

ABSTRACT

The field of Operations & Supply Chain Management (O&SCM) deals with large and complex structures. Evidence from practice suggests that management still runs in silos and decisions are often focused on specific functions as the totality of the problem and the impact on the broader organisation is not always understood. To manage such structures, managers have been investing in information technology to improve data availability and quality. Finally, good data is available with potential to enable holistic decision-making (DM). The field of analytics answers the need to transform data into information to support DM processes. Visual analytics rely specifically on visual representations to support DM processes. As visual analytics is still at its infancy, the aim is to identify what types of visual analytics has been used in empirical research, to support what decisions and its impact in O&SCM context.

Evidence based literature review, also known as systematic literature review (SLR) method is used to review 41 papers.

The most common type of visual analytics identified is modelling, mapping and visual interfaces between data and managers. These most often support Plan and Make type decisions. Vast majority of applications are identified as positive, enabling better understanding of the problem, greater management involvement in the process and better communication.

Future research is needed to define the term “visual analytics” as the field is still at its infancy. Development and empirical testing is required of whether the identified visual tools are an enabler for holistic decisions in the O&SCM context.

Keywords:

Operations management, decisions, visual tools, impact, holistic

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To Heather Simpkins for doing an amazingly fast proof-reading of my work, making me realise how bad my grammar is.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
DM	Decision Making
DSS	Decision Support Systems
ERP	Enterprise Resource Planning
ETO	Engineer-to-Order
GUI	Graphical User Interface
IT	Information Technology
MPC	Manufacturing Planning and Control
MRP	Materials Requirement Planning
MRP II	Manufacturing Resource Planning
MTF	Make-to-Forecast (manufacture-to-forecast)
MTO	Make-to-Order (manufacture-to-order)
MTS	Make-to-Stock (manufacture-to-stock)
O&SCM	Operations and Supply Chain Management
OM	Operations Management
OR	Operations Research
PCA	Principal Component Analysis
SC	Supply Chain
SCM	Supply Chain Management
SLR	Systematic Literature Review
SOM	Self-organising map (data mining technique)
VIM	Visual Interactive Modelling

1 Introduction

1.1 The managerial challenge

Theory suggests that supply chain management (SCM) is an integrated and overarching activity connecting departments and business partners (Christopher 2011). Evidence from practice suggests it is still run in silos (Godsell et al. 2010) and supply chain (SC) decisions are often fragmented at the departmental level (Raisinghani and Meade 2005).

SCs can be viewed as sets of plans, to source, make and deliver processes (SCOR reference model[1]) in an interconnected network of businesses focused on the provision of products/services required by the end customer (Christopher 2011; Harland et al. 2004). SCs are large and complex and it can be difficult for management to know where to focus their attention. Practically speaking, this is usually focused on their function, as the impact on the broader SC is not always visible or understood.

For instance, there are many anecdotal examples from the retail sector. Manufacturers can offer the retailers discounts to buy bulk volumes of products at the end of a financial period to help meet sales targets. From a procurement perspective this can seem like a great opportunity and appears to save the retailer money. However, if the item is large and bulky, such as disposable nappies, the cost of storing the products could outweigh the price saving. A good decision for the procurement function becomes a bad decision for the SC. To move towards holistic decisions, SC managers require information that gives them a better visibility of the impact of a functional decision on the SC. Game Theory suggests that, given better information, rational managers will tend to make decisions for the greater good of the group rather than the individual manager, department or function (Neumann and Morgenstern 1947). It follows that, also if given better information, SC managers will tend to make decisions

[1] SCOR Reference Model is based on three main components: Process Modelling; Performance Measurement; and Best Practice. Process modelling framework breaks down into five management processes: Plan; Source; Make; Deliver; Return. (source: http://supply-chain.org/scor)

for the greater good of the SC rather than their individual function. To make holistic decisions, managers require holistic information. To create holistic information, there is a need for holistic data (Ackoff 1989; Choo 1998). Historically there has been a paucity of holistic data cross the supply chain. Data have existed within functional silos (Brun and Zorzini 2009), been of poor quality (Niemi et al. 2007) and have not been easy to access (Kannan and Tan 2010).

To address these issues, management has invested in IT infrastructure (e.g. Enterprise Resource Planning[2] systems, data warehouses) to improve the quantity and quality of, and accessibility to, data and information.

Organisations that have invested in IT are now in a position where they can begin to use the data, to create information that can be used to make more holistic SC decisions. The process of creating information from data and using it to support decision making is specifically regarded as analytics (Davenport 2006).

1.2 The rise of visual analytics

This section presents the relationship between analytics, OR and O&SCM, focusing on the power of visual analytics.

The increased availability of good quality data and the resultant opportunity to make better use of them has created the emergent field of analytics (Davenport 2006). Analytics is, however, still an immature field and lacks consensual definition (Liberatore and Luo 2010).

One possible definition of analytics is provided by Davenport and Harris (2007, p.7):

"The extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions."

[2] Enterprise Resource Planning (ERP) is an integrated software solution built to support basic internal business processes of a company (Robert Jacobs and Weston Jr. 2007).

This suggests that analytics go beyond just analytical methodologies or techniques, and can be defined as the scientific process of transforming data into insight for making better decisions. Liberatore and Luo (2010, p.323) state that analytics *"…is having an increasing impact on decision making and performance management within many organizations, and it is sometimes viewed as a source of competitive advantage"*.

The field of Operations Research (OR) provides many analytical tools and consider their application in practice to aid decision making to be the field of analytics.(Davenport 2006; Marchand & Peppard 2013; Liberatore & Luo 2010)

Operations Management (OM) and the expanded discipline of Operations & SCM (O&SCM) has historically been the context in which many OR techniques are applied, this includes analytics as they lend themselves well to aid the O&SCM manager in making holistic decisions. However, one of the key challenges of analytics is convincing the end-user to trust its outputs to make decisions (Davenport 2006; Marchand and Peppard 2013; Niemi et al. 2007). The use of ore visual ways to present the output of analysis is critical as people find it easier to process visually presented information (e.g. animations, graphics, plots, or charts) (Castellanos-Garzón et al. 2013; Davenport 2006; Hutchison and Mitchell 2008; Kang and Stasko 2012; Marchand and Peppard 2013). This has led to the emerging importance of the sub-field of analytics, known as visual analytics. (Hutchison and Mitchell 2008). Visual analytics success can be inferred by analogy to the relatively recent success of industrial simulation, mostly due to the ability to depict and animate models (Chiu and Russell 2011; Kasprzyk et al. 2013). Visual analytics involves much more than just using visual representations to understand data better. It is an approach that combines data analysis, human cognition and visualisation that enables both discovery and detection of the unexpected and expected within large amounts of data and information (Hutchison and Mitchell 2008). This approach to analytics enables dashboards which are recognised as one of the most effective means of supporting management activity (Chiu and Russell 2011; Liberatore and Luo 2010; Russell et al. 2009)

1.3 Research problem

This presents an opportunity to explore how visual analytics can be used to enable holistic SC decisions from an organisational perspective. This is the broader research question. For the purpose of the Systematic Literature Review (SLR) the aim is identifying the types of analytical tools, techniques or methods for visual data representation that have been used to support decision-making in O&SCM, the types of decisions that they support and its impact.

As illustrated in Figure 1, the SLR focus on the domain of visual analytics and the role that this plays in decision-making in an O&SCM context. In this way the broader domain of analytics is delimited to visual analytics, but draws on its OR roots and the broader domain of decision-making is delimited to decisions in an O&SCM context.

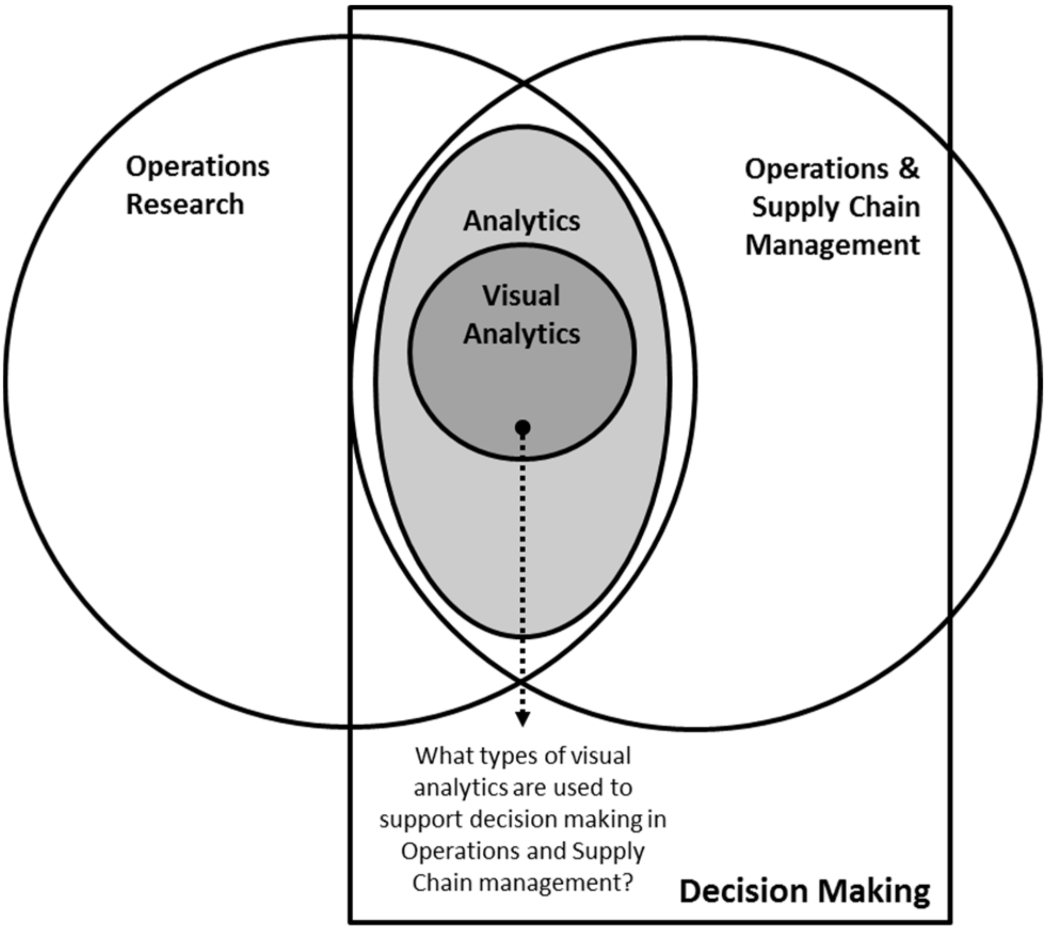

Figure 1 To illustrate the map of relevant fields

1.4 Structure of the thesis

This section introduces the structure of the thesis. Figure 2 illustrates the structure at the chapter level, followed by a brief explanation of each chapter.

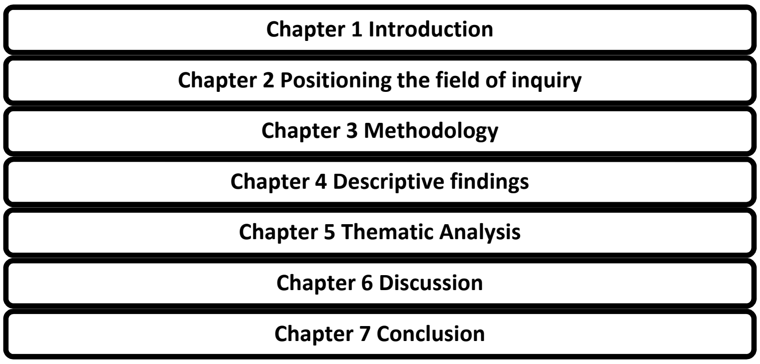

Figure 2 Dissertation structure

Chapter 2 introduces the main fields of knowledge related to the use of visual analytics in O&SCM DM. The main purpose of this chapter is to explore the literature and to set the scene for a systematic approach to specific literature in order to answer the specific review questions presented at the end of the chapter.

Chapter 3 presents the protocol followed through this SLR. It describes five main phases: Panel selection; Design of search strategy; Establishment of a selection criteria and quality appraisal standard; Data analysis; and Data synthesis. The main purpose of this chapter is to make this SLR as objective and scientific as possible by minimising bias.

Chapter 4 characterises the selected body of literature that remained after performing the systematic selection according to the explicit set of criteria stated in chapter 3. Key publication features are characterised, such as trends in publications per annum, keyword analysis, number of articles per journal, the respective quality and country of origin of the first author. Additionally, trends in methodology per annum and on overall level are given.

Chapter 5 summarises the main themes covered by the selected body of literature. Following the review questions, three main sections are presented.

Firstly the focus falls on different types of visual analytics discussed in each paper, followed by the different types of decisions that they support, and ending with an analysis of the impact of visual analytics. Each of the sections analyses the literature in a cross-sectional manner and its main purpose is to present the emergent themes from the selected body of literature that are relevant to the review questions.

Chapter 6 focuses on the discussion of the findings and its relevance to the research question and sub-questions. A section discusses the connection between the different types of visual analytics, the respective decisions that they support as well as the impact. This is summed up into a conceptual framework. This chapter closes with answers to the review questions and a conclusion.

Chapter 7 concludes this SLR by reviewing the research objectives, contribution to knowledge, critique, personal learning and finally gives an overall summary.

1.5 Conclusion

This section concludes the introduction. The main point is the presentation of the managerial challenge. Given that SCM is supposed to be an overarching and holistic activity spanning across companies' borders, limited information has been causing lack of visibility which consequently has been driving local decisions. Companies have invested in IT over the last decades to improve the quality of data which is available today. Data are most of the time useless unless they are transformed into information and insight, which is the purpose of analytics. Analytics is a rising field spanning across a number of other fields such as data mining, cognitive psychology, mathematics and mostly OR. Since communication and problem understanding is often one of the key issues in management (Liberatore and Luo 2010), visual analytics provide a user-friendly interface between the data and the manager. Visual analytics are supported by visuals, data representations, graphics and models representing reality or concepts which are designed to support the process of decision making.

The aim of this SLR is to review literature applying different types of visual analytics used for decision-making in an O&SCM context, what are the different decisions that they support and finally what is the impact of visual analytics on these decisions.

2 Positioning the Field of Inquiry

2.1 Introduction

Figure 3 illustrates the structure of this chapter. After a brief introduction, the chapter is broken down into several sections presenting the seminal building blocks for the development of the argument for using visual analytics for decision-making in O&SCM.

The focus is on positioning this argument in specific fields of O&SCM, Analytics and DM. The chapter starts with the presentation of the underlying concepts of data and information in 2.2 which is critical to understanding the arguments of this thesis. 2.3 focuses on analytics which evolves into the specific sub-field of visual analytics described in 2.3.1, finishing with different types of analytics in 2.3.2. Decisions are discussed in 2.4 focusing specifically on types of decisions in the context of O&SCM. This chapter is summed up in 2.5 along with the SLR questions.

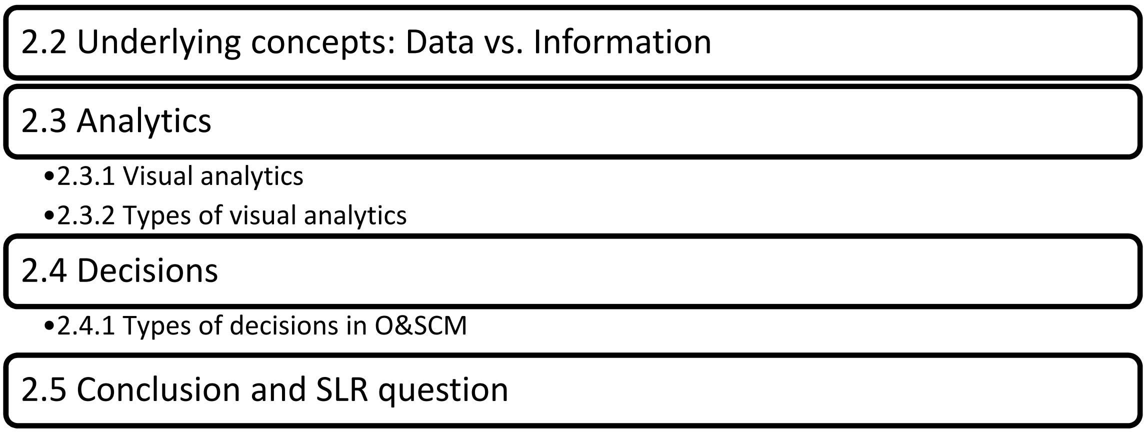

Figure 3 Positioning the field of inquiry chapter structure

2.2 Underlying concepts: Data vs. Information

This section explores the underlying concepts that integrate the hierarchical set of data, information, knowledge and wisdom; and its relationships. It is critical to understand how each differ from each other.

From a systems thinking perspective (or info-engineering) they are part of a defined structure. As an initial approach based on Ackoff's (1989) from data to wisdom hierarchy.

Information in its raw form is data, i.e. without any relationship between facts or statements (Berthold and Hand 2007; Rowley 2007). Those data, otherwise meaningless, are transformed into information by using specific processes that find their relations (Rowley 2007).

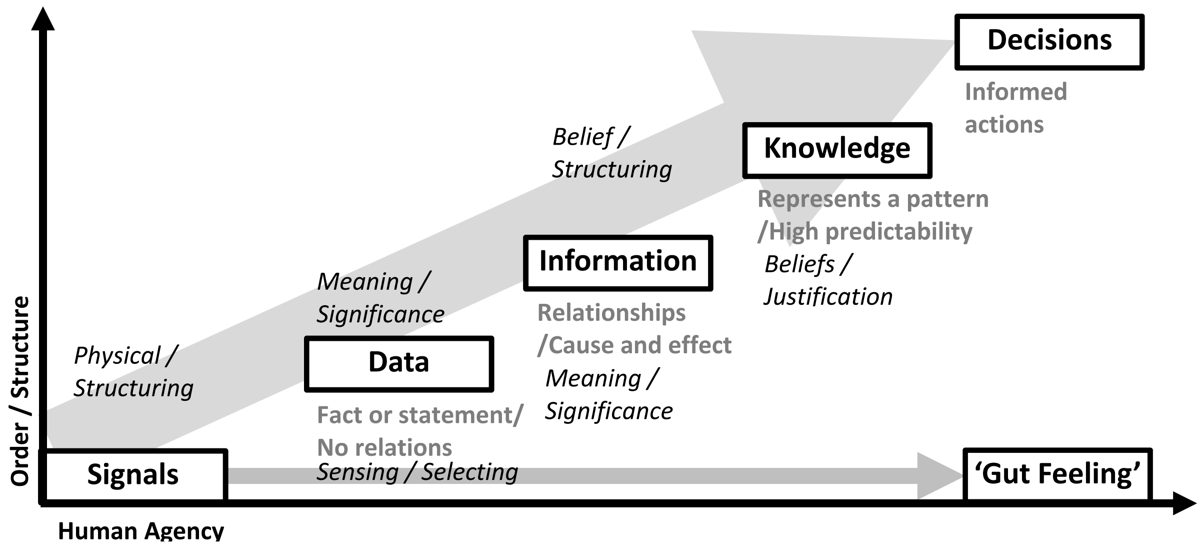

Figure 4 From signals to decisions – based on Ackoff (1989), Choo (1998) and Rowley (2007)

The above sequence is part of a broader hierarchy consisting of: signals; data; information; and knowledge (Choo 1998) illustrated in Figure 4. From the basic signals to knowledge, both human agency as well as the order/structure increases.

On one hand, the element 'decisions' is the next step of informed actions based on previous knowledge. On the other hand, 'gut feeling' decisions are the highest human agency and lowest order-structure, which often substitutes decisions as informed actions.

It is commonly accepted that quality information is precious and vital (Choo 1998). Most human activity focuses on recording data so those data can be used to create information to finally enable knowledge and wisdom that can be used to drive informed actions, i.e. decisions. This leads towards analytics as the step from data to information, which assists the decision-making process.

2.3 Analytics

Analytics and data-mining are closely related, where data mining is in its most basic definition the science of knowledge discovery which purpose Hutchison and Mitchell (2008, p.v) put as: *"Knowledge discovery holds the promise of insight into large, otherwise opaque datasets."*

Analytics might be seen as the transformation processes of data into information to support the process of DM. Analytics are therefore the discovery and communication of meaningful patterns and associations found in data to identify opportunities or relationships among different factors that can be used to approach DM (Davenport 2006; Han and Kamber 2006). Analytics rise from a number of theories, for example control theory, decision theory, network theory or system theory (Davenport 2006; Han and Kamber 2006; Hutchison and Mitchell 2008; Keim et al. 2008).

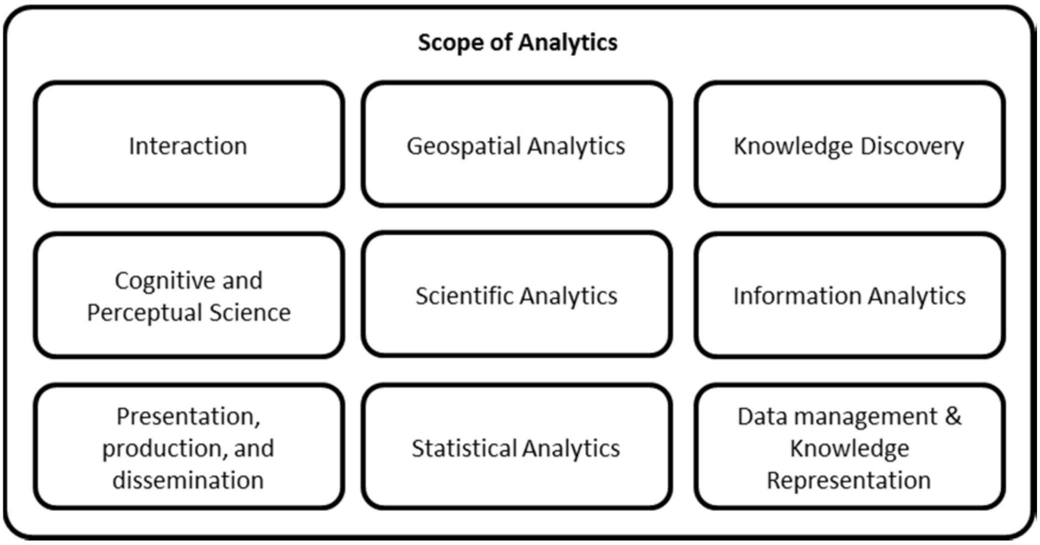

Figure 5 The Scope of Analytics (adapted from Keim et al. 2008)

The scope of analytics is very broad (Figure 5) and as an emerging field there is no consensus about its precise definition (Hutchison and Mitchell 2008; Liberatore and Luo 2010). The definition of analytics is unclear as it changes from field to field; for example, Gulledge and Shavusholu (2008) refer to it as a control technique, linking it to control theory. Davenport (2006) define it as an improved way of using information for trends that can be defined. Others define analytics simply as a method of knowledge discovery (Pearson 2002; Trkman et al. 2010). The adopted definition of analytics for this SLR is provided by Davenport and Harris (2007, p.7) as: *“the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions.”*

Analytics have a broad nature, merging several different fields into one making it challenging to use (Davenport 2006; Marchand and Peppard 2013; Niemi et al. 2007). This presents the opportunity to explore one of the most powerful sub-fields of analytics: visual analytics (Keim et al. 2008). Visual analytics tend to change the paradigm that separates data analysis from data visualisation towards a new paradigm of direct interaction, i.e. real-time interactivity with the end-user (manager in this case).

2.3.1 Visual analytics

One of the key challenges of analytics is convincing the end-user to trust its outputs (Davenport 2006; Marchand and Peppard 2013; Niemi et al. 2007). Given that people find it easier to process visually presented information (e.g. graphics, plots, or charts) visual representations are crucial for successful analytical applications (Castellanos-Garzón et al. 2013; Davenport 2006; Hutchison and Mitchell 2008; Kang and Stasko 2012; Marchand and Peppard 2013). Visual analytics are sometimes referred as visual data-mining because of the communalities between analytics and data mining (Keim et al. 2008).

Visual analytics rise from a broad range of fields, from decision analysis, to expert systems, system design or simulation. One of the most important elements of visual analytics is their interactivity, which links into the human-computer interaction field and process control (Davenport 2006; Han and Kamber 2006; Hutchison and Mitchell 2008; Keim et al. 2008). Finally, fields of data mining and consequently the knowledge discovery field (Pearson 2002; Trkman et al. 2010).

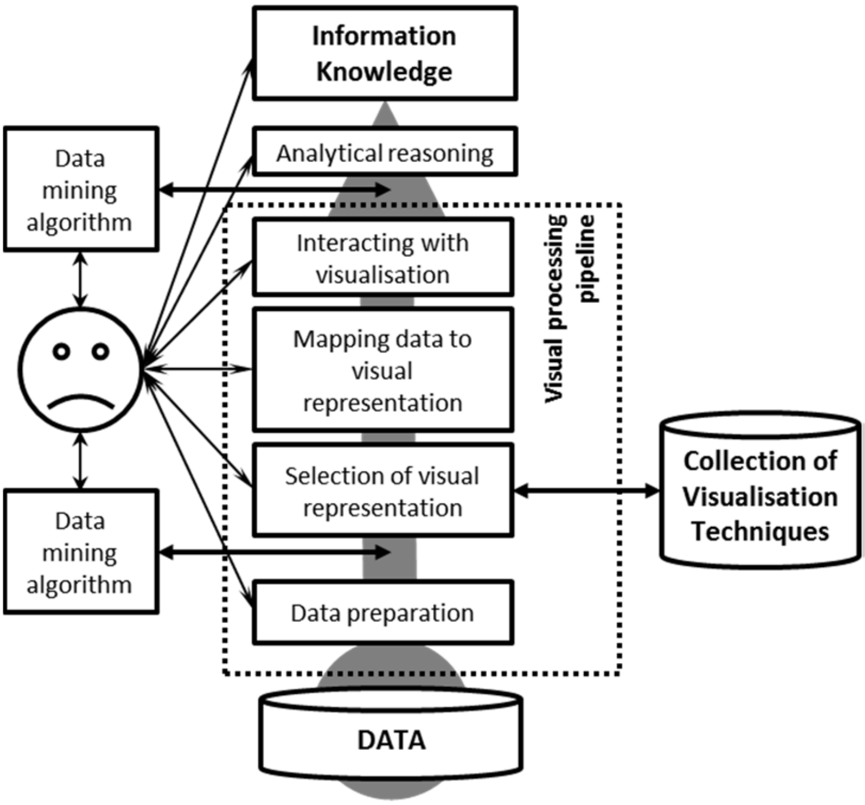

Figure 6 Visual analytics as a human-centred interactive analytical and discovery process (adapted from Hutchison and Mitchell 2008)

Figure 6 illustrates a human-centred approach to the process of visual analytics the visual processing pipeline prepares raw data so they can be analysed using data transformation algorithms, followed by the selection of visual representations from a collection of existing techniques. The last steps of the visual processing pipeline are mapping data into visual representation and interacting with visualisation, so both analysts and managers can proceed with the iterative process of analysis. Finally, analytical reasoning about the findings that result in information and knowledge that are useful for decision-making takes place.

There are a number of different types that can be considered as visual analytics due to their wide nature: diagrams, graphics, representations of data and interfaces and a range of mapping techniques, models and even data mining methods based on spatial transformations that gain from interaction with humans for their high cognitive capacity and visual pattern recognition ability.

2.3.2 Types of visual analytics

It is challenging to set up a taxonomy of visual analytics because of the broad nature of the field. However, some known tools used in analytics projects can be described as being visual analytics due to its visual nature and purpose of supporting the process of transformation from data to information to support a decision or a problem.

Decision tables are a way to model logical thinking and to create a certain structure of actions, conditions and rules to support decision-making (Vessey 1991). Decision Trees are a decision support tool that uses graphs or models that look like a tree often including probabilities of certain outcomes, costs and utilities and can be used to display algorithms and processes widely used in OR for decision analysis (Dey 2012).

Flow diagrams or flowcharts are a diagram type used to represent algorithms and processes step by step with a number of different symbols to illustrate different types of steps (Wu et al. 2011). Cause and effect diagrams, also known as Ishikawa diagrams, are causal diagrams that show causes of a specific event (Dey 2012).

Graphics in this particular case are any form of visual data representation that cannot be classified in other categories, such as mapping, which goes in a separate category of visual analytics (Vessey 1991). Probabilistic graphical model is a particular type of graphics that focus on conditional dependences between random variables (Wooff et al. 2002). Inductive System Diagram Technique is a case-specific methodology developed in the paper by Burchill and Fine (1997). Interpretative Structural Modelling enables the structuring of ‘elements’ based on any transitive relationship similar to PERT diagrams (Lu and Druzdzel 2009).

Mapping concerns the creation of a graphic representation of information using any form of relationship between data (Brožová et al. 2008). Object Oriented

Modelling is also known as object-oriented programming which is a modelling paradigm used in computer programming and can be used in a modular fashion using interacting objects as modelling blocks (Biswas and Narahari 2004).

Principal Component Analysis (PCA) is a statistical procedure based on graphical analysis and correlations between variables (Hodgkin et al. 2005).

Agent Based simulation is a sub-field of simulation that relies on autonomous agents representing individuals or collective entities with certain attributes to represent some reality (Hilletofth and Lättilä 2012).

SOM & Clustering are two types of pattern recognition techniques that are often used as a tool to represent and organise data in a machine + man process (Samarasinghe and Strickert 2013). Similarly, User-interfaces or graphical user interfaces (GUI) are a very particular type of visual analytics since they encompasses systems designed to provide decision-makers with outputs, e.g. dashboards (Hu et al. 2012).

Finally, VIM is a visual representation of objects and systems using graphical language, e.g. UML (Kirkpatrick and Bell 1989).

These examples of visual analytics can be categorised into a more generic fields as listed in Table 1.

Table 1 Types of visual analytics

Analytics Category	
Diagrams	It is often a two or three dimensional symbolic representation of information using visualisation techniques.
Graphics or Plots	Graphics or plots are graphical techniques for representing data where two or more variables are show with some relationship in between.
Interfaces	Interfaces are the point of interaction between the user and the software, system or hardware.
Mapping	Mapping is the creation of graphical representations of information using spatial relationships.
Modelling	Modelling is a process of creating representations of data into a generic model, often used to analyse data and system requirements necessary to support business and organisations.
Other types	Facing the plethora of visual techniques, statistics based on spatial solutions or clustering can fall into the category of visual analytics. However, there are many other possibilities.

2.4 Decisions

Decisions are one of the core elements of management (Choo 1998). Consequently, DM has been a hot topic in many different contexts (e.g. Li, Yamaguchi and Nagai 2007; Raisinghani and Meade 2005; Sanayei, Farid Mousavi and Yazdankhah 2010; Wu and Barnes 2011; Yang, Wen and Wang 2011). The challenge of DM escalates as the number of choices multiplies and it can be both rational (analytical) and irrational and emotional (Stanovich and West 2000).

In the pursuit of good decisions and more efficient data and information processing, people start to rely on decision support systems (DSSs) of different types (e.g. Collins, Ketter and Gini 2010; Delic, Douillet and Dayal 2001; Popovič et al. 2012). These systems have evolved, from the basic calculator to the artificial intelligence (AI) systems enabled by modern technology. Most daily managerial decisions are made using what is known as bounded rationality (Choo 1998; Ireland and Webb 2007; Schoenherr and Swink 2012; Simon 1987; Steptoe-Warren et al. 2011). Managers often make decisions based on experience and 'gut feeling' that is detached from any hard data or evidence due to time constraints, limited information and the information-processing ability of the mind (Binmore 2009; Choo 1998; Simon 1987; Simon 1969; Stanovich and West 2000).

Decision theory, in particular game theory, suggests that given economically rational agents, the quality of one's decision increases as the amount of information available tends towards perfection (Helmer 1963; Nash 1950; Ross 2011; Smith 1982). In theory, a rational agent provided with perfect information will be able to make the optimal decision (Nash 1950). When relying on external decision support, DSSs are equipped with methods that improve the probability of a good decision being made. These DSSs allow a combination of raw data, documents and user knowledge (Delic et al. 2001). These methods are regarded as analytics (Davenport 2006).

2.4.1 Types of decisions in O&SCM

Operations Management (OM) and the expanded discipline of Operations & SCM (O&SCM) has historically been the context in which many OR techniques to support DM processes are applied. One possible reference model to describe processes in O&SCM context is the SCOR reference model[3] illustrated in Figure 7.

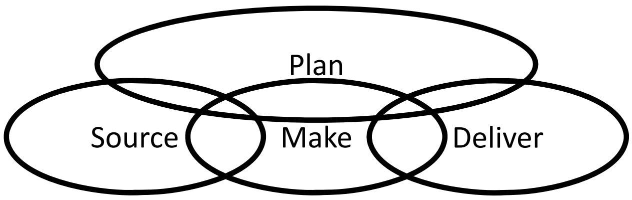

Figure 7 SCOR Reference Model

The SCOR model is based on three main components: Process Modelling; Performance Measurement; and Best Practice. The process modelling framework breaks down into five management processes: Plan; Source; Make; Deliver; Return. From the O&SCM perspective, breaking it up into different elements presents different types of decisions and managerial problems. For example, in Source, supplier selection is often a complex problem as the number of suppliers can range from none to unbearable numbers that require some sort of analytical support for an efficient selection process. In the Make category, adopting different manufacturing strategies is also a complex decision with a number of factors, implications and constraints. Regarding Deliver, the management of orders, transport and distribution are best achieved when supported by machine and analytical tools. Finally, Plan focuses on balancing aggregate demand and supply to manage Source – Make and Deliver relying on analytical methods.

2.5 Conclusion and SLR question

The focus for management is on O&SCM and the potential of visual analytics as an enabler of holistic decisions. Operations Management (OM) and the

[3] (source: http://supply-chain.org/scor)

expanded discipline of Operations & SCM (O&SCM) has historically been the context in which many OR techniques are applied. Part of these OR techniques are now called analytics. The most powerful sub-set of analytics is visual analytics as it benefits from the high interactivity with the end user making use of human cognitive ability and flexibility.

Visual analytics in O&SCM can support the selection of strategic drivers, explore business opportunities and market segments and achieve internal alignment both through verification of hypotheses as well as the discovery of meaningful trends or patterns that can challenge the way decisions are made.

Despite the technological potential, visual analytics has not been exploited to its full potential in business practice (Marchand and Peppard 2013) and it has been a rare research topic in SCM (Niemi et al. 2007). When considering the organisation or its SC, things can quickly escalate and grow in complexity.

The SLR focuses on the following question:

What types of visual analytics are used to support DM in O&SCM?

There are three sub questions:

1. What types of visual analytics are used?
2. What O&SCM decisions do they support?
3. What impact do they have on the DM process and outcome?

The unit of analysis is twofold, as illustrated in Figure 8, first at the firm level and second at the supply chain level. The former is comprised of the plan, source, make, and delivery processes (SCOR reference model); the latter is the extended supply chain that looks externally to include customers and suppliers.

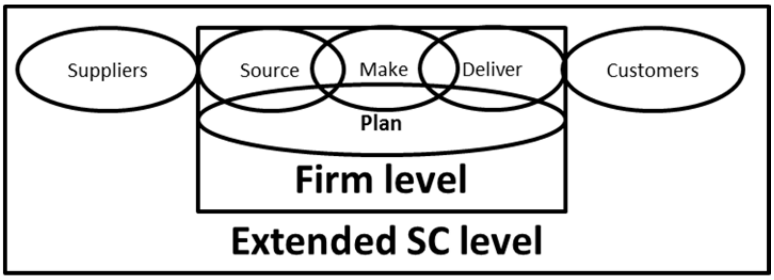

Figure 8 To illustrate the unit of analysis

The study focuses on papers that present the results of the practical application of visual analytic tools in an O&SCM context to aid O&SCM decisions in practice. This could include implementation of visual analytics within the ‘live’ O&SCM of an organisation or equally the use of off line analytical techniques (e.g. simulation) that aid DM for the ‘live’ O&SCM.

Chapter 3 now presents the methodology used, specifically the SLR process which is a methodology to review literature while minimising bias and arriving objectively to a research gap or pertinent research question for further research.

3 Methodology

3.1 Introduction

This chapter justifies the choice of the SLR as a methodology, stating the procedure and protocol followed. The main purpose of having a search protocol is for it to be clear enough so the procedure can be repeated, consequently achieving the same results. Five main phases constitute the systematic review procedure:

1) Panel selection
2) Design of search strategy
3) Establishment of a selection criteria and quality appraisal standard
4) Data extraction
5) Data synthesis

Consequently, the methodology chapter is structured as illustrated in Figure 9. Note that the establishment of a selection criteria and quality appraisal are split into two separate sections for clarity.

3.2 The systematic review process

- 3.2.1 Review panel
- 3.2.2 Design of search strategy
- 3.2.3 Selection criteria
- 3.2.4 Quality appraisal
- 3.2.5 Data extraction
- 3.2.6 Data synthesis

3.3 Conclusion and observations on the systematic process

Figure 9 Methodology chapter structure

3.2 The systematic review process

The purpose of the SLR is to locate existing studies, select and critically evaluate contributions related to the review questions (Tranfield et al. 2003).

Originally SLR's came from the medical field to encourage evidence-based knowledge development (Tranfield et al. 2003), the SLR process has been adapted to the management sciences as being a replicable, scientific and transparent approach seeking to minimise bias by systematically summarising and extracting all existing information about a phenomenon (Denyer and Tranfield 2009). SLR's are based on four fundamental steps after the selection of a panel. The process starts with the development of a review plan, followed by the selection and quality appraisal of the relevant literature. The next step focuses on the extracted literature, by analysing and synthesising it in a systematic fashion. The process closes with a report of the key findings, their contribution to answering the review questions and offers further research opportunities and implications for practice.

3.2.1 Review panel

The role of the review panel is to give advice, guide the researcher through the systematic review process and resolve issues regarding the inclusion and exclusion of articles (Tranfield et al. 2003). The panel can also recommend further literature. As listed in Table 2, the review panel is composed of three main groups: topic specialists; systematic review experts; and an information extraction specialist.

In the topic specialist's category, Dr Janet Godsell is the supervisor and topic advisor with expertise in OM, logistics and SCM as well as business performance management. Dr Johannes Fichtinger is also a topic advisor with background in OR (inventory control and quantitative modelling), risk and decision theory.

In the systematic review process category, Dr Marek Szwejczewski is the panel's chair and he and Dr Jonathan Lupson are both systematic review experts.

In the information extraction category, Heather Woodfield advises on searching academic databases and search query building.

Table 2 Systematic review panel

Person	Title/Department	Role
Janet Godsell	Reader, Cranfield School of Management	Supervisor: gives feedback on draft of the review
Johannes Fichtinger	Lecturer Cranfield School of Management	Topic Advisor: provides literature recommendations
Marek Szwejczewski	Reader, Cranfield School of Management	Panel Chair and systematic review expert: provides support on the search methodology
Jonathan Lupson	Lecturer, Cranfield School of Management	Systematic review expert: provides support on the search methodology
Heather Woodfield	Kings Norton library	Advices on searches and database management

3.2.2 Design of search strategy

Figure 10 outlines the adopted search strategy. First, identification of the keywords is mostly based on the previous scoping of the literature, described in 3.2.2.1. Next, the keywords are organised into search strings used for the literature extraction, described in 3.2.2.2. 3.2.2.3 discusses the databases used to search for the previously created search strings. After the identification of keywords, respective queries and where to look for (databases) search strings are tested. The first decision point is whether a relevant search is generated or not. The first relevance criteria is based on criteria described in 3.2.3 by scanning some of the results (no more than 10 each time). In case relevant results are not generated, the strategy is to broaden the query by excluding or changing logical restrictors (e.g. AND, NEAR, NOT), so the search strings and/or keywords are modified and the new search strings are tested until relevant literature is included in the results. The next step focuses on a narrowing down process, in case both relevant and irrelevant articles are included in the resulting batch. At this stage logical operators are added in order to focus and exclude some irrelevant fields or research but always following the first criteria for inclusion described in chapter 3.2.3.

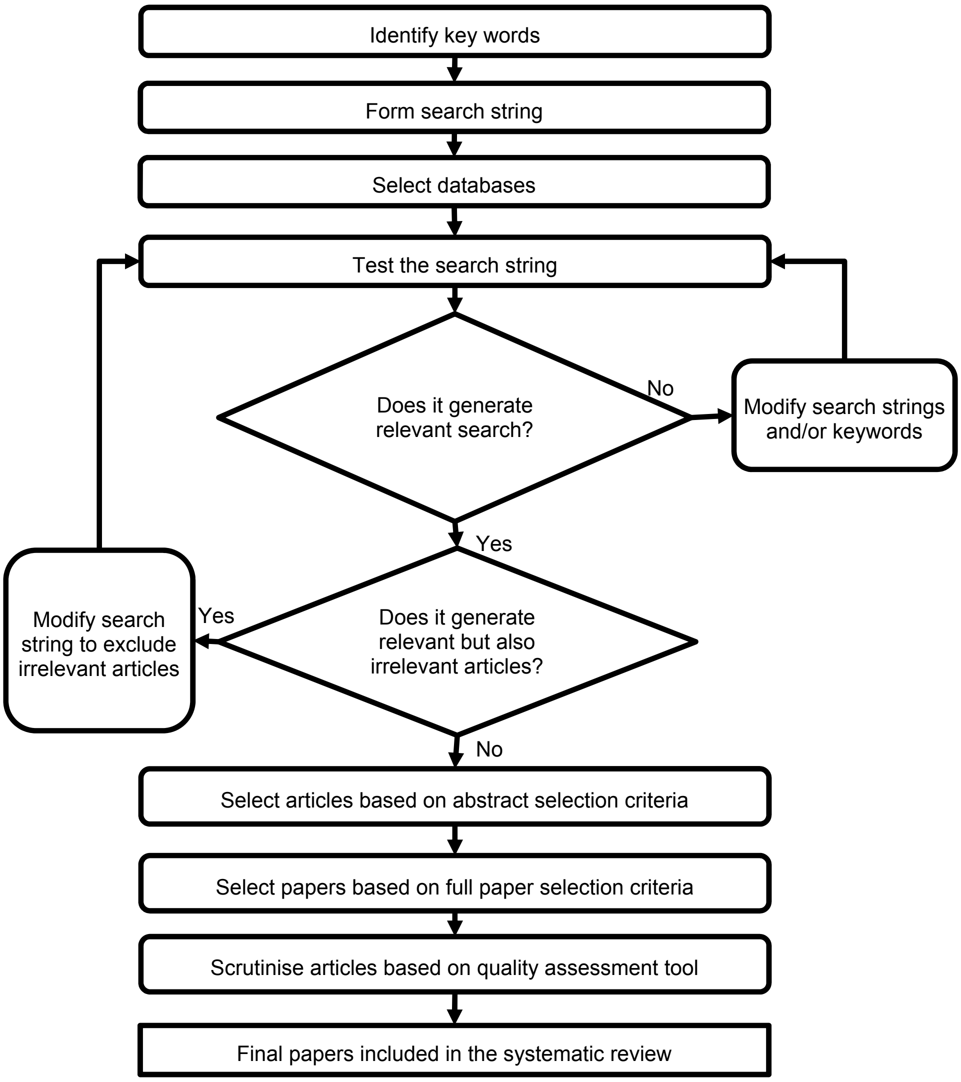

Figure 10 Search process

Once the search queries are fine-tuned to include mostly relevant literature, articles are selected based on exhaustive reading of titles and abstracts as described in 3.2.3. Following this, a second filtering phase focuses on the full paper reading. The outcome of this step is the final list of literature analysed in detail following the quality appraisal described in 3.2.4. After evaluating the quality of each paper, a third filtering phase takes place as only the most relevant and manageable number of papers go into the data extraction phase described in 3.2.5. This concludes the search process for the systematic review and the critical synthesis is initiated, as described in 3.2.6.

3.2.2.1 Keywords

The review questions contain three main components: analytics, DM and O&SCM. Table 3 lists on the left the main research fields related to the review questions (O&SCM, DM, and visual analytics) as discussed in chapter 2. Each of these components holds a number of related keywords that were obtained by combining the most frequent keywords found in the literature analysed during the scoping phase.

Table 3 Keywords

Field	Keywords
O&SCM	Supply chain, supply network, supply base management, demand chain, demand network, demand base, value chain, value network, logistics management, procurement management, sourcing management, purchasing management, operations management, production management
Decision-making	Decision support, decision making, decision system, decision process, decision framework, decision design, decision theory
Visual analytics	Visual, analytics, analytical, statistics, tool, prototype, dashboard, signals management, signals representation, signals transfer, signals mining, data technology, data systems, data infrastructure, data management, data modelling, data analysis, data analytics, data mining, data discovery, data transformation, data transfer, data representation, information technology, information systems, information infrastructure, information management, information modelling, information analysis, information analytics, information mining, information discovery, information transfer, information representation, knowledge technology, knowledge systems, knowledge infrastructure, knowledge management, knowledge model, knowledge analysis, knowledge discovery, knowledge transfer, knowledge representation

3.2.2.2 Search string

Derived from the above keywords, Table 4 lists the search string used to search the databases described in 3.2.2.3. The four sub-strings listed in Table 4 were connected using the “AND” operator. The only variation of this string was when using EBSCO Business Source Complete database which uses a different proximity operator (i.e. w2 instead of w/2). The search was performed on the title, abstract and keywords levels.

Table 4 Search query

Logic	Field	Query
AND	O&SCM	((supply OR demand OR value) w/2 (chain* OR network* OR base)) OR (logistics OR procurement OR sourcing OR purchasing OR operations OR production) w/2 management
AND	Decision-making	Decision w/2 (support OR making OR system* OR process* OR framework* OR design OR theor*)
AND	Visual analytics	Visual OR analytic* OR tool* OR prototype* OR dashboard* OR statistic* OR ((signal* OR data OR information OR knowledge) w/2 (technology OR system* OR infrastructure* OR manag* OR model* OR analy* OR mining OR discovery OR transform* OR transfer* OR representation*))
AND	Empirical research type	(empiric* OR “case stud*”)

3.2.2.3 Databases

The databases ABI/INFORM, EBSCO and Scopus were consulted to find the relevant literature. Both ABI/INFORM and EBSCO Business Source Complete are two of the most comprehensive business databases, covering a wide ranging time period. Scopus is an especially relevant database for SCM and OR. All three databases also include publishers' databases. Some overlap was expected between databases, but felt necessary in order to guarantee a comprehensive search of the literature by including the major databases.

Table 5 Initial search results

Database	Raw results
SCOPUS	804
ABI/INFORM	1615
EBSCO Business Source Complete	546
Total	2965

An initial search on Scopus resulted in 804 hits, ABI/INFORM in 1615 hits and EBSCO Business Source Complete in 546 hits using the search string from Table 4 and summarised in Table 5. These initial results include any type of publication (e.g. articles, conference papers, reviews, and others) in any language, giving a total of 2965 items. All three sets from SCOPUS, ABI/INFORM, and EBSCO were extracted into RIS format (with abstracts) and imported into the chosen reference management software (Mendeley). The results significantly scaled down when only articles were filtered, resulting in a more manageable number of results which is described further and in more detail in 3.2.3.

The overlap analysis was performed after importing all results into the reference management software using the Mendeley tool "Check for duplicates". Out of the total, 50 were duplicates which, after the merge, resulted in 25 sets. It is important to note that some of the hits were incomplete and required some data-cleaning before the analysis (e.g. incomplete fields and wrong paper type classification) prior to excluding mistakenly classified conference papers and working papers. Finally, by filtering two star or higher journals according to Cranfield's Journal Recommendations for Academic Publication (9^{th} ed, 2012) the final number of papers before title and abstract reading totalled 1123.

3.2.2.4 Cross-referencing and recommendations

An additional source for relevant literature is the cross-referencing of identified relevant articles as well as recommended articles by the review panel. These articles, however, go through the same approval process of selection criteria and quality assessment as described in 3.2.3.

It is likely that papers from other fields or with a slightly different focus (e.g. not case-based) improve the argument and the process of answering the review questions of this thesis, namely reviews and surveys of the use of visual analytics in practice (assuming that visual analytics can be interpreted as any visual methods, e.g. Visual Interactive Modelling (VIM)). These are picked up by analysis of references featuring papers selected for quality appraisal through the systematic process.

3.2.3 Selection criteria

As the search strings produce literature that include the correct keywords but not necessarily be relevant to the review questions, further inclusion and exclusion criteria need to be established before the full text is considered. These inclusion and exclusion criteria are used in the first part of the search strategy when only the title and abstract of the articles are reviewed. Table 6 lists the basic criteria for article selection while Table 7 expands the understanding of the relevance for the review questions criteria specifically. Only articles that fulfil all selection criteria pass the full article review.

Table 6 lists the generic and quasi-objective filtering criteria. Except for their relevance to the review questions criteria, the remaining six criteria considered to be objective are:

1. Language;
2. Scientific field;
3. Type of publication;
4. Research type;
5. Paper type; and
6. Paper quality;

These criteria were used to narrow down the number of initial hits from 2965 results (including some duplicates) to 1123 which passed the title and abstract level analysis. Finally, the number converged at 66 items using the inclusion criterion of relevance for the review questions explained in Table 7.

Table 6 Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion	Rationale
Relevance for review question	Relevant	Not-relevant	Answering the review question (Expanded in Table 7)
Language	English	All except English	English can be considered as the universal language for academic publications
Scientific field	SCM; OM; OR	All other scientific disciplines	This is the scientific discipline in which the review questions is located
Type of publication	Academic peer reviewed papers Practitioner papers	Non-peer reviewed academic literature	To maintain a high quality standard only peer reviewed articles are considered. Practitioner papers are also helpful to answer the review question
Research type	Empirical papers	Conceptual papers	To gain insight on types of analytics used in the O&SCM context, the focus is on empirical literature
Paper type	Published journal articles	Conference papers Working papers	Only journal articles are reviewed, ignoring conference papers since journal publications are likely to have a higher quality standard than conference papers.
Paper quality of academic literature	2, 3 and 4 star journals	1 star journal	To ensure a minimum level of academic literature, Cranfield School of Management ranking was used (2012).

Since this research is focused on the empirical research related to visual analytics to drive management decisions in O&SCM, the remaining social sciences and humanities fields are outside the scope.

The criteria of relevance of some given papers are challenging to set up in an objective way and bias must be acknowledged. To clarify, the criterion or relevance is expanded in Table 7. With regard to the review questions, the extent to which the article discusses any (one or more) examples of visual analytics is applied in practice for DM in O&SCM. Visual analytics and what can be classified as analytics have been defined in chapters 1 and 2. Briefly, analytics can be defined as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions" (Davenport & Harris 2007, p.7). A more generic definition could even be, 'the scientific process of transforming data into insights for making better decisions', while the subfield of visual analytics is analytics as defined previously but relying explicitly on any form of visual representation. If the abstract or article does not mention or discuss any form of visual representation as an outcome of the application of analytics, it is considered irrelevant.

Abstract level analysis for relevance, as listed in Table 7, follows the rationale that any quality abstract features the purpose and implications as well as referring to what the paper is about.

Table 7 Relevance criteria according to the review questions

Relevance	Inclusion criteria	Exclusion criteria
Types of visual analytics	Reference to anything that can be classified as visual analytics	Nothing is mentioned that can be classified as visual analytics
What O&SCM decisions do they support?	Reference to any specific decision type or area of management supported by analytics	The purpose of the paper misses the managerial challenge
What impact analytics have?	Reference to any practical implications	Practical implications are missing

As is sometimes apparent, relevant articles seem to fulfil all the inclusion criteria in the title and abstract level; but the full texts of the articles which remain after the investigation of title and abstract is further examined in relation to using the same criteria listed in Table 6 and also most of Table 7 as it focuses on whether it is relevant or not for the review questions.

The remaining list of papers passes on to the next step focusing on the quality appraisal, as discussed in 3.2.4.

3.2.4 Quality appraisal

Once the relevant papers are identified, they are assessed regarding their quality. Due to their differences in terms of purpose and methodology, a generic appraisal criteria is applied, as listed in Table 8. The criteria are based on the review questions of this SLR and assessed on a scale from 1 (Low level) to 3 (High level). In the quality appraisal, all criteria are given equal weight. A cut-off level is determined once all relevant studies have been assessed to ensure that a significant, but still manageable, number of publications are included.

In case a single paper scores a high level in all five criteria, equal to 15 (3*5), it is included. The cut-off point is an average paper scoring at least 2 in each criterion. The quality appraisal table with the selected literature can be seen in Appendix A.

Table 8 Quality appraisal criteria

ID	Empirical papers	1	2	3
Q1	Is the purpose of the research adequately established?			
Q2	Are the practical implications adequately discussed and described?			
Q3	Are analytics adequately described and justified?			
Q4	Does the writer adequately discuss the impact of analytics on the decision types in focus?			
Q5	Are alternative approaches to the decisions in focus considered?			
	1= Low level, 2= At an acceptable level, 3= High level			

3.2.5 Data extraction

Once a piece of literature has been deemed appropriate, based on the quality appraisal, it is imported into the citation management software Mendeley and relevant data is extracted to support the subsequent analysis and synthesis. The data extraction form (Table 9) developed for this purpose is considered a flexible tool and may be adapted during the review in order to support an analysis that allows for the development of a critical argument (Dixon-Woods et al. 2006). The data extracted from the selected literature and used for this SLR can be seen in Appendix B.

Table 9 Data extraction form

Category	Details	Data
Citation	(Title, Author(s), Journal/Source, year, abstract, keywords	
Study background	Type of research (empirical, practitioner)	
	Managerial challenge / problem	
	Types of decisions in focus	
Methodology	Approach	
	Data collection and analysis methods(s)	
Evidential contribution	Research question	
	Key findings	
	Limitations and scope for further research	
	Type of analytics used	
	Practical implications (especially for decision in focus)	
Synthesis	Key contribution(s) to review questions' answers	
	Comments/observations/notes	

3.2.6 Data synthesis

The information extracted from the final papers selected for the review is used to present a coherent synthesis. Generically, the purpose of data synthesis is twofold: first, to provide a clear analysis of the literature reviewed; and second, to identify scope for further research. The intended outcome is a conceptual framework about the use of analytics for decision-making in an O&SCM context, featuring types of analytics and related types of decisions to support further empirical research.

The main elements under analysis are types of analytics and types of decisions and the relationship between them. The connection between the two is the impact of different types of analytics on different types of decisions. This constitutes the three sub-chapters of the synthesis chapter.

The synthesis relies on tables and cross-thematic analysis comparing and contrasting different themes. The descriptive chapter lists the decision typology, analytics typology and practical implications for each contribution. The thematic chapter presents the main themes emerging from the previously analysed body of literature.

Finally, a critical analysis draws on the descriptive and thematic chapters by analysing the content, linking different themes in order to build a conceptual model to support further research.

3.3 Conclusion and observations on the systematic process

This section concludes the methodology chapter by going through the paper selection process in a systematic search.

The number of items for further analysis remained high (2111 items) after considering only the language, type of publication and paper type criteria. The number was, however, significantly reduced after the application of the paper quality of academic literature criteria described in 3.2.3, dropping to 1123 items.

After this step, the focus was on relevance for the review questions (Table 7). This step required title and abstract reading which reduced the results to only 66 items, which were added along with three more based on references. Full paper reading and quality appraisal therefore focused on 69 papers resulting in 28 excluded and 41 kept. The full selection from the beginning to end of this process is illustrated in Figure 11.

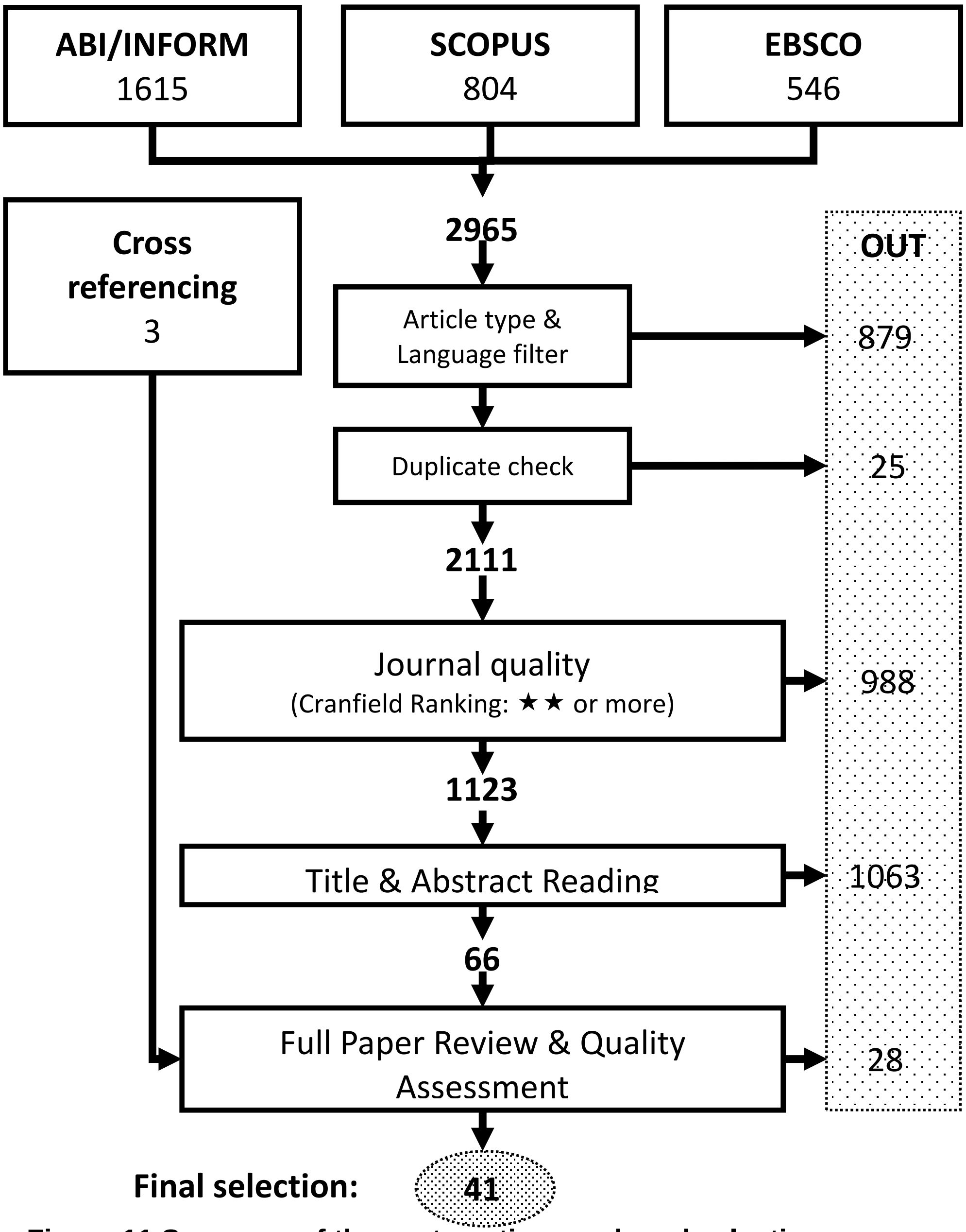

Figure 11 Summary of the systematic search and selection process

4 Descriptive Findings

4.1 Introduction

In this chapter the characteristics of the 41 journal articles included in the SLR process are described. 4.2 presents the basic descriptive, such as frequencies per year, number of articles per journal and the respective quality ranking, keyword analysis by frequency, closing with the country of origin of the first author. 4.3 contains the descriptive of methodologies adopted in the selected body of literature over years. The chapter closes with 4.4 that sums up chapter 4.

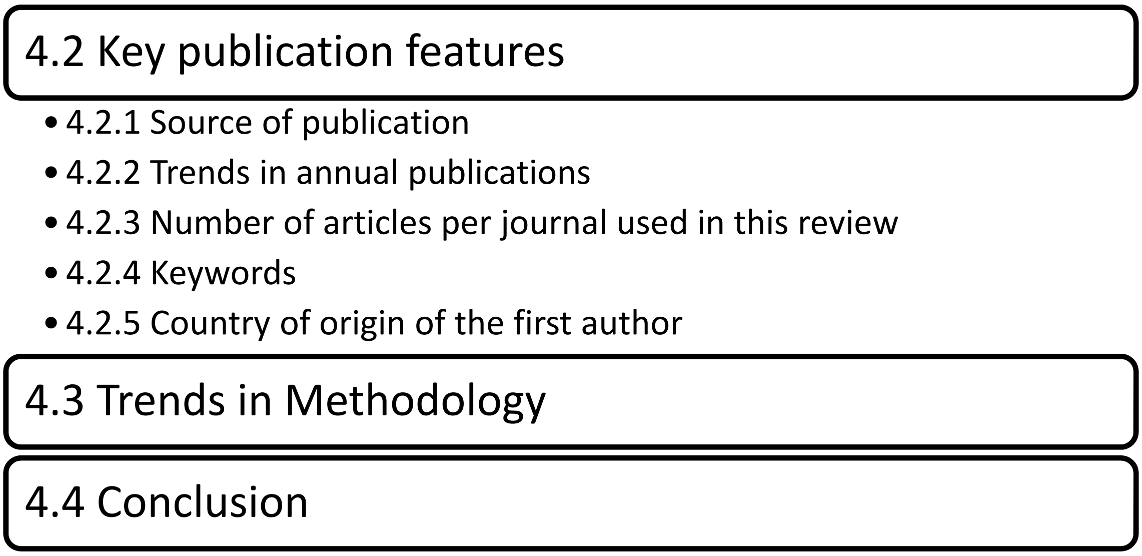

Figure 12 Descriptive Findings chapter structure

4.2 Key publication features

This section focuses on basic descriptives, such as the frequency analysis over years as well as by journal against the respective quality ranking (Cranfield SOM 2012) of the 41 selected publications.

4.2.1 Source of publication

Three main databases ABI/INFORM, EBSCO and Scopus were searched to find the selected literature. Both ABI/INFORM and EBSCO Business Source Complete are two of the most comprehensive business databases, covering a wide ranging time period. Scopus is especially a relevant database for SCM and OR. As illustrated in Figure 13, six papers are exclusive to EBSCO Business Source, 20 to ProQuest and two to Scopus. Between EBSCO, ProQuest and Scopus there is an overlap of four articles while six are between EBSCO and ProQuest only. This total number is enriched with three references being manually added which were located by cross-referencing. For full list of articles and source of publication see Appendix C.

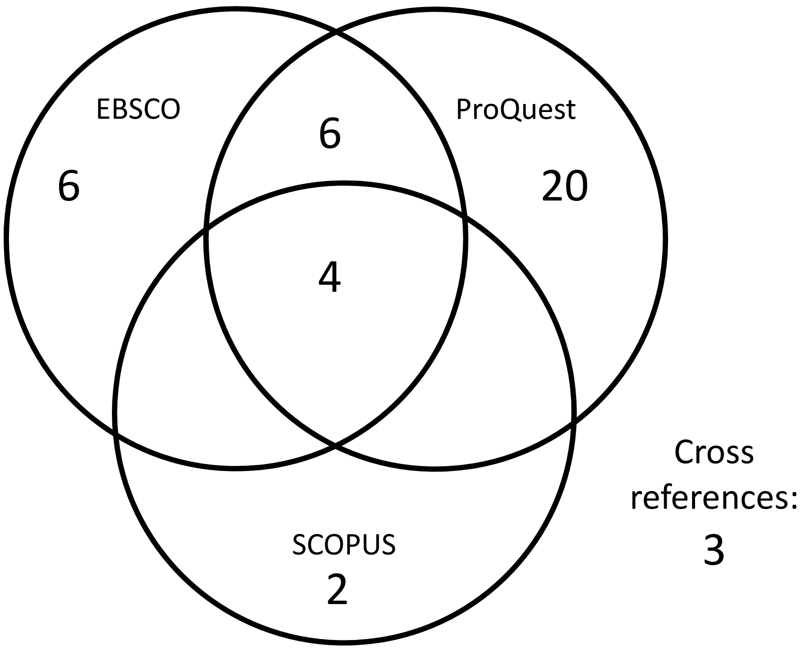

Figure 13 Source of publication

4.2.2 Trends in annual publications

As illustrated in Figure 14, the earliest selected publication is from 1978 after which follows a five year gap. From 1984 to 2013 the publication trend is stable with one or two articles, except for years 1988, 1996, 2002 and 2007 with no publications, and 2011 and 2012 with four publications each. The trend appears to be stable with a very subtle increase over the years 2011, 2012 and an incomplete 2013.

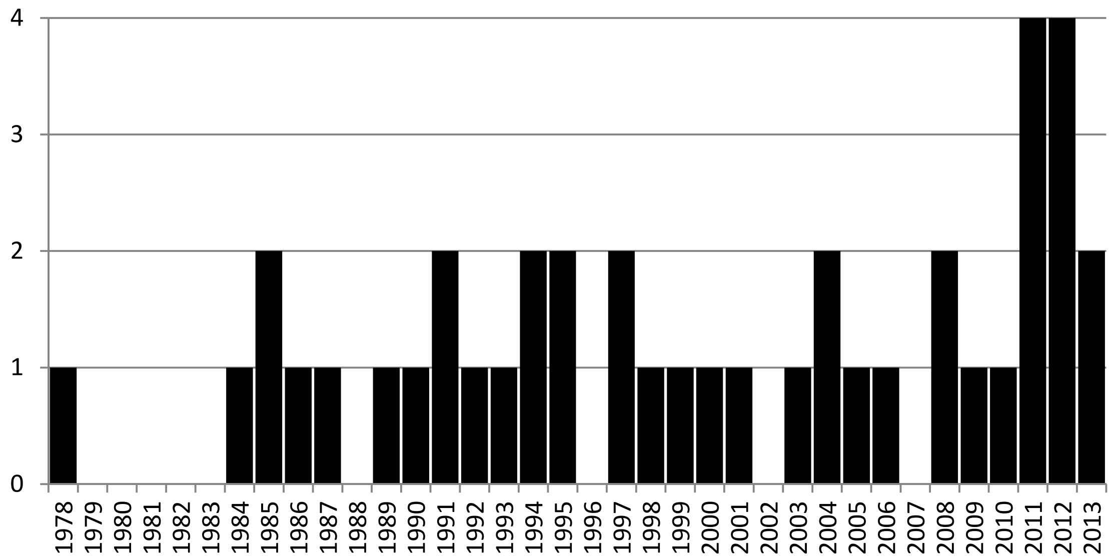

Figure 14 Number of publications per year (selected)

4.2.3 Number of articles per journal used in this review

As listed in Table 10 (descending order of paper frequency), this SLR focuses on 41 papers from 15 different journals all ranked from two to four stars according to Cranfield's Journal Recommendations for Academic Publication (9th ed, 2012). According to the chosen ranking system, the impact of publications is ranked against a star scale from one to four. Specifically, one star journals are considered to be national, two stars are internationally recognised, three stars are internationally excellent and finally four star journals are world leading. Only 12 out of the 41 are two star journals.

The breadth of publications spans the disciplines of OM, OR, decision sciences, management sciences, (decision support) systems, information management, and finally specifically SCM. This specificity suggests that the SLR inclusion criteria extracted papers from journals covering the pre-set fields of interest encompassing the review questions: O&SCM, OR and DM.

Table 10 Articles per journal and respective Cranfield SOM ranking

Journal	#	Ranking
European Journal of Operational Research	10	3
Journal of the Operational Research Society	5	2
Interfaces	4	2
International Journal of Production Research	4	3
Decision Sciences	3	4
Management Science	3	4
Decision Support Systems	2	3
International Journal of Operations & Production Management	2	3
Journal of Manufacturing Technology Management	2	2
British Journal of Management	1	3
IEEE Transactions on Systems, Man & Cybernetics: Part A	1	2
International Journal of Information Management	1	2
International Journal of Production Economics	1	3
Production, Planning & Control	1	2
Supply Chain Management: An International Journal	1	3
Grand Total	41	

4.2.4 Keywords

The selected articles contain a total of 452 unique keywords – the top 20 are listed in Table 11. Keywords are useful to quickly define the contents and the field of a given paper as well as some specifics such as method. They are used widely in databases as content tags to help quick searching and effective query building. Since authors must always provide a close/relevant and carefully matched set of keywords to make the work more visible, they can be considered as descriptive of the sample. On the global level, the most frequent category (keyword) was management science/operations research with 25 hits, followed by studies (as an alternative to case studies) and DSSs with 21 hits each. The remaining set of keywords relate to the three fields of interest: empirical studies in the field of O&SCM using OR to drive evidence based decision-making.

Table 11 Top 20 keywords used in the selected literature

Top 20 Keywords	#
Management science/operations research	25
Studies (alternative to Case Studies)	21
Decision support systems	21
Computers	17
Software & systems	17
Operations research	16
Decision making	13
Experimental/theoretical treatment	12
Business And Economics-Management	7
Experimental/theoretical	7
Decision making models	6
Case studies	6
Management science	5
Simulation	5
Supply chain management	4
Mathematical models	4
Production planning	4
Company specific/case studies	4
Experiment/theoretical treatment	4
Production planning & control	4
Other keywords	252
Total unique keywords	452 in 41 articles

4.2.5 Country of origin of the first author

The country of origin of the first author is critical for any SLR. As listed in Table 12, the US is the most represented with 13 articles (almost one third), second is the UK with seven, followed by India, Canada and Belgium with 3 contributions each. All the remaining countries are only represented by one publication each. The clear dominance in some specific regions of the world can mean a significant bias and must be acknowledged. A total of 24 contributions, i.e. more than half, come from an English speaking country. For full list of articles and country of origin see Appendix C.

Table 12 Country of origin of the first author

Country	#	Percentage
USA	13	32%
UK	7	17%
India	3	7%
Canada	3	7%
Belgium	3	7%
Sweden	1	2%
Slovenia	1	2%
Greece	1	2%
China	1	2%
Spain	1	2%
Turkey	1	2%
Taiwan	1	2%
Germany	1	2%
Singapore	1	2%
Australia	1	2%
Japan	1	2%
Portugal	1	2%
Grand Total	41	100%

4.3 Trends in Methodology

This section describes the major trends in methodology followed in the selected literature.

One of the selection criteria was including empirical literature only. However, one paper discussing the use of what can be classified as visual analytics is not specifically case-based or an empirical paper. It was accepted as an exception because its focus is one of the key issues related to visual analytics. Specifically this is the paper by Vessey (1991) which is a literature survey without empirical application. All the remaining 40 publications are empirical which break down into single case-based research (30) and multiple case (Ackermann and Belton 1994; Kayis and Karningsih 2012), surveys (Burchill and Fine 1997; Kirkpatrick and Bell 1989) and experimental studies (Browne, Curley and Benson 1997; Chau and Bell 1995; Huysmans et al. 2011; Jain, Ramamurthy and Sundaram 2006; Lu and Druzdzel 2009; Zmud 1978) as listed in Table 13.

Table 13 Trends in methodology

Methodology			Number of papers
Empirical	Case based	Single	30
		Multiple	2
	Survey		2
	Experimental		6
Conceptual	Literature survey		1
Total			41

Figure 15 presents the same perspective per annum, which shows that there is no obvious pattern in the adopted methodology which are evenly distributed over the publication pattern, with exceptions made for small samples (one or two) such as the conceptual paper by Vessey (1991) and two survey-based contributions (Burchill and Fine 1997; Kirkpatrick and Bell 1989).

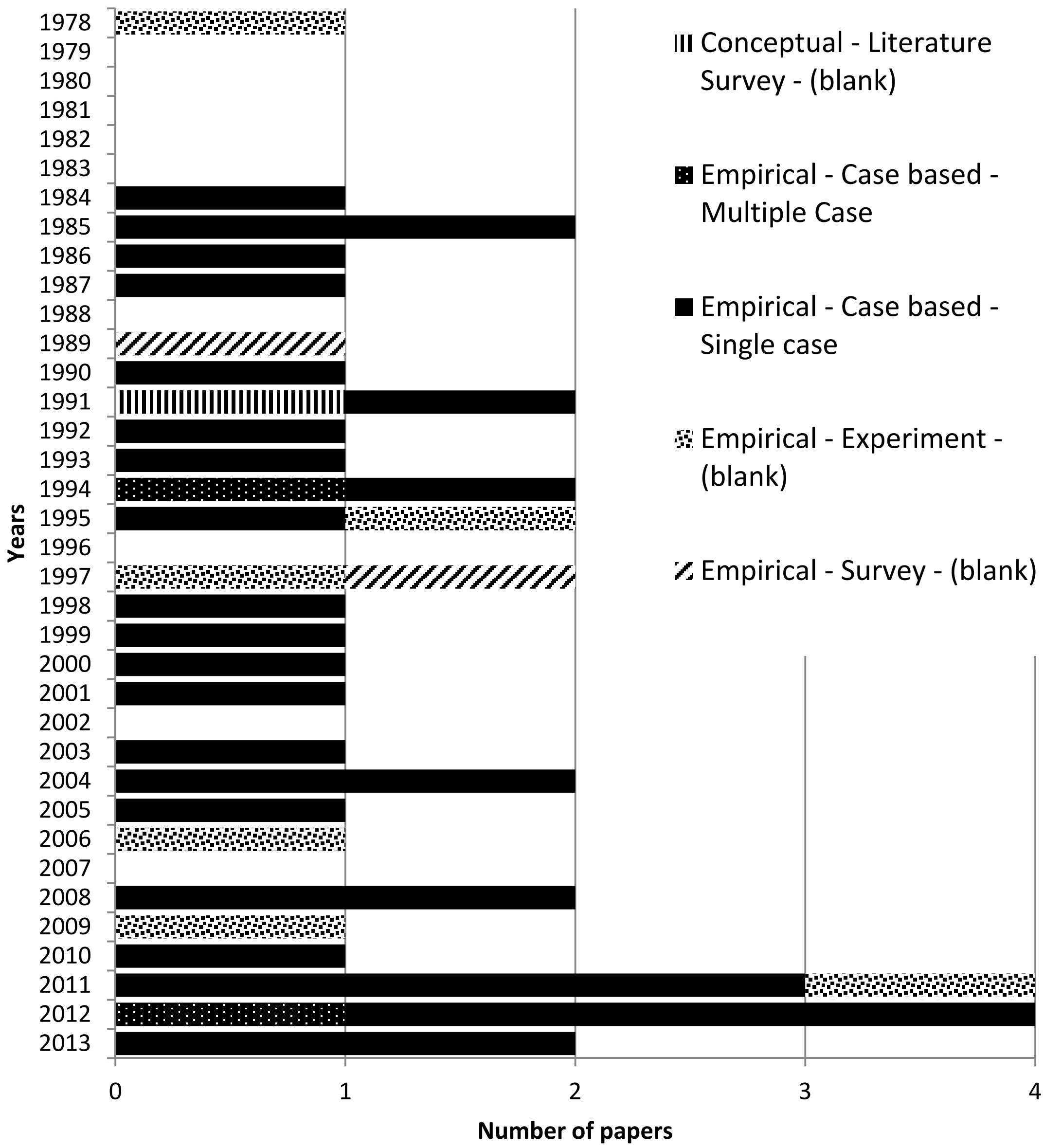

Figure 15 Trends in methodology over the years

4.4 Summary

This section concludes the chapter about the descriptive findings which focuses on characterising the sample systematically selected according to the protocol described in chapter 3. The main segments covered are the key publication features and trends in the methodology.

Regarding the key publication features there are a number of key ideas. Firstly, most of the selected literature is original from the ProQuest database (20 articles). Secondly, the selected literature exhibits a stable tendency of publication from 1978 to July 2013 with a subtle increase over the last three years with an average rate of one or two articles per year. Thirdly, the selected 41 papers come from 15 different journals all ranked from two to four stars according to Cranfield's Journal Recommendations for Academic Publication (9^{th} ed, 2012), and 29 papers are from journals ranked as three and four star. Fourthly, the top three keywords provided by the authors used to position the publication are 'Management science/operations research', followed by 'Studies' (alternative to case studies) and finally 'Decision support systems'. Finally, regarding the country of origin of the first author, the most represented are the US and UK with 32% and 17% of the selected literature respectively and more than half are English-speaking countries.

About trends in methodology, the vast majority (78%) are case-based papers as expected, while 15% are experiment-based. The distribution of adoption towards different types of methodology does not exhibit any significant changes chronologically.

Chapter 5 now focuses on the main themes covered by the selected body of literature against the review questions.

5 Thematic Analysis

5.1 Introduction

This chapter focuses on the thematic analysis. Four main sections follow this introduction as illustrated in Figure 16.

5.2 O&SCM Decisions

- 5.2.1 Types of ‘plan’ decisions
- 5.2.2 Types of ‘source’ decisions
- 5.2.3 Types of ‘make’ decisions
- 5.2.4 Types of ‘deliver’ decisions
- 5.2.5 Types of ‘return’ decisions
- 5.2.6 Non-Specific Decisions

5.3 Types of visual analytics

- 5.3.1 Categorisation of different types of visual analytics
- 5.3.2 Types of an analytics, respective field and theories

5.4 Impact of visual analytics

5.5 Conclusion

Figure 16 Thematic analysis of chapter structure

Firstly, 5.2 presents the decisions and managerial challenges found in the selected body of literature. The SCOR reference model is used to structure the sections into plan processes (5.2.1), source processes (5.2.2), make processes (5.2.3), deliver processes (5.2.4), and return processes (5.2.5). Finally, the remaining articles are described in the non-specific decisions 5.2.6.

Secondly, 5.3 classifies the different types of visual analytics found in the selected body of literature. The identified types of visual analytics are categorised (5.3.1) and presented against the respective theory and field (5.3.2).

Finally, 5.4 focuses on the impact of visual analytics. The chapter is brought to a close with a chapter summary in 5.5.

5.2 O&SCM Decisions

This section reviews the type of SC decisions made against the widely recognised Supply Chain Operations Reference (SCOR[4]) model. The model breaks down into source, make, deliver, plan and return processes. The SCOR framework was developed as an industry neutral, operations and supply chain framework aimed at standardisation. It is widely recognised as an industry standard and is a natural way to consider the type of SC decisions. SCOR has five main processes. Four forward facing processes (plan, source, make, and deliver) and one backward facing process (return).

Table 14 lists papers against the decision classification framework. The most popular focus is on Plan functions with 16 contributions, followed by Make processes with 13 contributions. The remaining decisions groups are not so dominant with six papers addressing delivery processes, two papers for both Source and Return processes. Some of the contributions were impossible to classify against the reference model, with 11 contributions being classified as "non-specific"; these are mostly experiment-based decisions and a survey.

[4] SCOR model is based on three main components: Process Modelling; Performance Measurement; and Best Practice. Process modelling framework breaks down into five management processes: Plan; Source; Make; Deliver; Return. (source: http://supply-chain.org/scor)

Table 14 Decision types in focus

Reference	Plan	Source	Make	Deliver	Return	Non Specific	#
Zmud (1978)						✓	1
Levary and Kalchik (1984)	✓		✓				2
Bell (1985)	✓			✓			2
Hurrion (1985)	✓		✓	✓			3
Lembersky and Chi (1986)			✓		✓		2
Day et al. (1987)	✓						1
Kirkpatrick and Bell (1989)						✓	1
Naruo et al. (1990)			✓				1
New et al. (1991)	✓						1
Vessey (1991)						✓	1
Grabowski and Sanborn (1992)			✓				1
Hess (1993)			✓				1
Ackermann and Belton (1994)	✓						1
Walker (1994)			✓				1
Carravilla and de Sousa (1995)	✓						1
Chau and Bell (1995)						✓	1
Browne et al. (1997)						✓	1
Burchill and Fine (1997)			✓				1
Özdamar et al. (1998)	✓						1
Siskos et al. (1999)						✓	1
Völkner and Werners (2000)	✓						1
Cortes et al. (2001)	✓						1
Willemain et al. (2003)						✓	1
Biswas and Narahari (2004)	✓			✓			2
Čižman and Černetič (2004)			✓	✓			2
Hodgkin et al. (2005)	✓						1
Jain et al. (2006)						✓	1
Kumar and Arbi (2008)	✓						1
Pal and Kumar (2008)		✓					1
Lu and Druzdzel (2009)						✓	1
Maliapen and Dangerfield (2010)	✓			✓			2
Cottyn et al. (2011)			✓				1
Huysmans et al. (2011)						✓	1
Persson (2011)	✓						1
Wu et al. (2011)						✓	1
Dey (2012)			✓				1
Hu et al. (2012)			✓				1
Kayis and Karningsih (2012)		✓	✓				2
Seret et al. (2012)				✓			1
Mangla et al. (2013)					✓		1
Wu et al. (2013)	✓						1
Grand Total	**16**	**2**	**13**	**6**	**2**	**11**	**50**

Additionally, some papers cover not only one decision type, but several, as illustrated in the Venn diagram in Figure 17. The highest overlap is between plan and delivery with three papers that focus on both decision types (Bell 1985; Biswas and Narahari 2004; Maliapen and Dangerfield 2010). The remaining overlaps are singular, with one article for plan and make (Levary and Kalchik 1984); one for plan, deliver and make (Hurrion 1985); one for source and make (Kayis and Karningsih 2012), and finally one for return and make (Lembersky and Chi 1986).

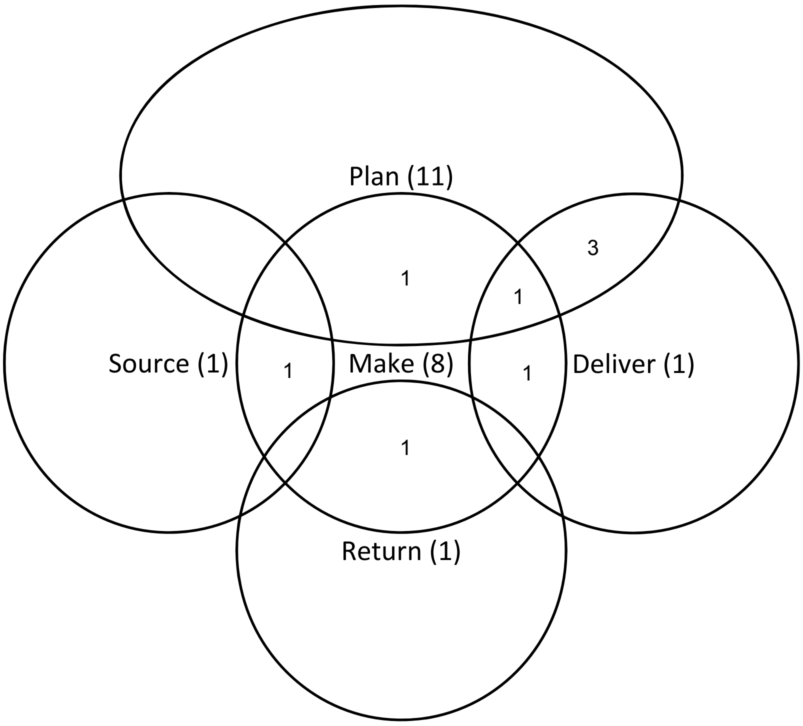

Figure 17 Contributions vs. SCOR Reference model

The following sections cover each of the decision types by category accordingly to the SCOR reference model, presenting and classifying the specific contribution and its focus.

5.2.1 Types of 'plan' decisions

Plan processes balance demand and supply to develop a course of action which best meets sourcing, production and delivery requirements. This function is the most represented in the selected body of literature with 16 contributions, as listed in Table 15.

Table 15 Decisions for plan processes

Decision type	Decision target	Article	#
Inventory Management (1)	Inventory Policy optimisation	Biswas and Narahari (2004)	1
Layouts (1)	Group layout definition	Levary and Kalchik (1984)	1
Performance Improvement (4)	Outsourcing	Kumar and Arbi (2008)	1
	Process Optimisation	Völkner and Werners (2000)	1
	Process Planning	Hodgkin et al. (2005) Maliapen and Dangerfield (2010)	2
	SC (re)design	Persson (2011)	1
Production Planning (5)	Manufacturing Capacity Planning	New et al. (1991)	1
	Production Optimisation	Bell (1985) Hurrion (1985)	2
	Production Scheduling	Özdamar et al. (1998) Carravilla and de Sousa (1995)	2
Delivery Planning (2)	Delivery Optimisation	Bell (1985) Hurrion (1985)	2
Resource Allocation (2)	Manufacturing Resource Allocation	Wu et al. (2013)	1
	Supply network optimisation	Cortes et al. (2001)	1
Strategic Planning (2)	Competitive analysis	Day et al. (1987)	1
	Group-Strategy development	Ackermann and Belton (1994)	1
Total			**16**

The most popular decision type is production planning (Bell 1985; Carravilla and de Sousa 1995; Hurrion 1985; New, Lockett and Boaden 1991; Özdamar, Bozyel, and Birbil 1998). Specifically for manufacturing capacity planning, New et al. (1991) use visual interactive models by using simulation in capacity planning. To optimise production through planning, Bell (1985) presents VIM as a technique for OR, focusing on production planning, queuing systems analysis, personnel training, job shop scheduling, traffic flow analysis, assembly-line design. For the same purpose of optimisation Hurrion (1985) focuses on planning for production, distribution and finance systems using a DSS based on visual interactive consensus. Finally, to schedule production, Carravilla and de Sousa (1995) focus specifically on production planning in a make-to-order company while Özdamar et al. (1998) describe a hierarchical DSS for production planning.

The second most popular decision type is performance improvement (Hodgkin et al. 2005; Kumar and Arbi 2008; Maliapen and Dangerfield 2010; Persson 2011; Völkner and Werners 2000). Two papers focus on process planning inside performance improvement: Hodgkin et al. (2005) carried out a case study applying a multi-person and multi-criteria DSS designed for stressful and time pressured environments, empirically tested in operations planning of day-care centre for adults with cerebral paralyse; Maliapen and Dangerfield (2010) investigated clinical pathways in a hospital using empirical clinical data of patient episodes, providing a DSS to improve and draw scenarios for service delivery. Focusing on outsourcing decisions, Kumar and Arbi (2008) rely on simulation, mapping and analysis of SC design for redesign purposes, mostly contributing to a better planning in SCM. For process optimisation, Völkner and Werners (2000) propose a DSS for business process planning, transferring the experience from project management or production process planning contexts into the business planning process. Finally, for SC design Persson (2011) implements and discusses an SC analysis tool based on simulation and the SCOR template to enable, besides many other SC improvements, better planning and SC design.

The remaining decision types are not so dominant. Two papers touch on delivery planning (Bell 1985; Hurrion 1985), two on resource allocation (Cortes et al. 2001; Wu et al. 2013) and two on strategic planning (Ackermann and Belton 1994; Day et al. 1987). The remaining decision types are represented by single papers on inventory management (Biswas and Narahari 2004) and layout planning (Levary and Kalchik 1984).

In detail, in the less dominant category, delivery planning is explored again by Bell (1985) who presents VIM as an technique for OR, while Hurrion (1985) focuses on planning distribution using a DSS based on visual interactive consensus. Resource allocation is covered by Wu et al. (Wu et al. 2013) focusing specifically on manufacturing resource allocation planning by taking a matrix-based Bayesian approach for manufacturing resources allocation planning in SCM, specifically a robust manufacturing resource allocation plan by solving a multi-criteria decision-making process. Yet in the resource allocation decisions, Cortes et al. (2001) explore supply network optimisation by presenting a DSS for planning telecommunication networks in the Andalusian region. Strategic planning, specifically group-strategy development, is considered by Ackermann and Belton (1994) who propose two distinct DSS systems to manage corporate knowledge experiences towards the development of strategy, planning, and DM in a wide variety of organisational settings.

Another paper discussing strategic planning, but focusing on competitive analysis, is the work by Day et al. (1987) who define strategy maps using a special representation method, which impacts on the planning at a strategic level, in an intra-industry competitive level. Finally, inventory management, specifically inventory policy optimisation, is discussed by Biswas and Narahari (2004) who address specifically the field of SCM providing a DSS based on object oriented modelling that also supports planning decisions by suggesting the location of bottling plants. Finally, for group layout definition decisions, Levary and Kalchik (1984) use a visual-based group decision-making process to plan a layout.

5.2.2 Types of 'source' decisions

Source processes procure goods and services to meet planned or actual demand and only two publications can be classified under this scope as listed in Table 16. Kayis and Karningsih (2012) focus on risk management, specifically source and make strategy selection by identifying supply chain risks using a tool which besides other elements, identifies supply base risk. Pal and Kumar (2008) in the category of supply base management proposes a model for vendor evaluation and selection.

Table 16 Decisions for source processes

Decision type	Decision target	Article	#
Risk Management (1)	Source and make strategy Selection	Kayis and Karningsih (2012)	1
Supplier management (1)	Vendor Evaluation and Selection	Pal and Kumar (2008)	1
Total			2

5.2.3 Types of 'make' decisions

Make processes transform product into a finished state to meet planned or actual demand and it is the second most represented segment in the selected body of literature with 14 papers as listed in Table 17.

Table 17 Decisions for make processes

Decision type	Decision target	Article	#
Equipment maintenance (2)	Diagnosing malfunctions	Naruo et al. (1990)	1
	Machine replacement	Walker (1994)	1
Inventory Management (1)	Stock reduction	Čižman and Černetič. (2004)	1
Layouts (1)	Group layout definition	Levary and Kalchik (1984)	1
Manufacturing (1)	Product development	Burchill and Fine (1997)	1
Performance Improvement (3)	Business and Engineering alignment	Hu et al. (2012)	1
	Manufacturing process and objectives alignment	Cottyn et al. (2011)	1
	Resource recovery	Lembersky and Chi (1986)	1
Piloting (1)	Real-time Shipboard piloting	Grabowski and Sanborn (1992)	1
Production Planning (1)	Production Optimisation	Hurrion (1985)	1
Project selection (1)	Group Project Selection	Hess (1993)	1
Risk Management (2)	Risk Mitigation strategy	Dey (2012)	1
	Source and make strategy Selection	Kayis and Karningsih (2012)	1
Total			13

The most popular decision type is focused on performance improvement (Cottyn et al. 2011; Hu et al. 2012; Lembersky and Chi 1986). Hu et al. (2012) explores the alignment between business and engineering decisions by proposing a corporate dashboard for integrated business decisions and engineering decisions in oil refineries. Cottyn et al. (2011) focus on a method to align manufacturing execution systems with Lean[5] objectives. Finally, for resource recovery, Lembersky and Chi (1986) optimise the use of raw material, specifically the development of a DSS for the best use of a given tree stem.

Second in the popularity scale are both equipment maintenance (Naruo et al. 1990; Walker 1994) and risk management (Dey 2012; Kayis and Karningsih 2012). For equipment maintenance decisions, Naruo et al. (1990) develop a knowledge-based DSS to diagnose malfunctions of production equipment and similarly, Walker (1994) explores a case for machine replacement using graphical analysis. For risk management, Dey (2012) develops a work in the field of production, planning and control doing project risk management using a multiple criteria decision-making technique. Kayis and Karningsih (2012) focus on identifying SC risks using a tool which, besides other elements, allows choosing between different source and make strategies, namely make-to-stock (MTS), make-to-order (MTO) and engineer-to-order (ETO).

[5] Lean, or Lean Manufacturing is a set of principles that considers the expenditure of resources that is not adding value as a waste (Womack et al. 2007).

Amongst the less well represented decision types is inventory management (Čižman and Černetič 2004), layout definition (Levary and Kalchik 1984), manufacturing (Burchill and Fine 1997), piloting (Grabowski and Sanborn 1992), production planning (Hurrion 1985), and project selection (Hess 1993). Specifically, for inventory management and stock reduction, Čižman and Černetič (2004) focus on the production of veneers, specifically a user-friendly DSS for cutting stock. For group layout definition Levary and Kalchik (1984) present an unusual way for the group decision-making process supported by visual techniques for layout finalisation in an office. For manufacturing, and specifically product development, Burchill and Fine (1997) generate theory focused on product concept development and quality function deployment (QFD). For real-time shipboard piloting Grabowski and Sanborn (1992) focus on the process of piloting a ship, and the inherent reasoning and real-time operational control system. For production planning and optimisation Hurrion (1985) writes about planning for production, distribution and finance systems using a DSS based on visual interactive consensus. Finally, for group project selection Hess (1993) analyses research and development project selection applications using visual sensitivity analysis.

5.2.4 Types of 'deliver' decisions

Deliver processes provide finished goods and services to meet planned or actual demand and include management of orders, transportation and distribution. Deliver processes are covered by six papers from the selected literature, as listed in Table 18.

Table 18 Decisions for deliver processes

Decision type	Decision target	Article	#
Inventory Management (2)	Inventory Policy optimisation	Biswas and Narahari (2004)	1
	Stock reduction	Čižman and Černetič (2004)	1
Marketing (1)	Direct Marketing	Seret et al. (2012)	1
Performance Improvement (1)	Process Planning	Maliapen and Dangerfield (2010)	1
Delivery Planning (2)	Delivery Optimisation	Bell (1985), Hurrion (1985)	2
Total			**6**

The two most popular decision types are inventory management (Biswas and Narahari 2004; Čižman and Černetič 2004) and delivery planning (Bell 1985; Hurrion 1985). For inventory management, specifically inventory policy optimisation, Biswas and Narahari (2004) address the field of SCM providing a DSS based on object oriented modelling – its practical case is ready product inventory optimisation and location of bottling plants. For stock reduction Čižman and Černetič (2004) focus on the production of veneers, specifically a user-friendly DSS for cutting stock. For delivery planning and optimisation Bell (1985) presents VIM as an technique for OR using an instrumental case of an ethylene complex focusing on its delivery, while Hurrion (1985) focuses on planning for production, distribution and finance systems using a DSS based on visual interactive consensus.

Finally, the least represented decision types are marketing decisions (Seret et al. 2012) and performance improvement (Maliapen and Dangerfield 2010). For direct marketing decisions Seret et al. (2012) present a self-organising-map method to generate a demand profile for direct marketing, using a case of the entertainment industry and delivery of matched preference marketing contents. For process optimisation Maliapen and Dangerfield (2010) investigate clinical pathways in a hospital using empirical clinical data of patient episodes, providing a DSS to improve and draw scenarios for service delivery.

5.2.5 Types of 'return' decisions

Return processes focus on returning or receiving returned products for any reason. As listed in Table 19, only two of the selected papers focuses on return processes (Lembersky and Chi 1986; Mangla et al. 2013). Mangla et al. (2013) analyse flexible decision strategies for a sustainability-focused green product recovery system, focusing on the return activities and performance improvement. Lembersky and Chi (1986) optimise the returns and use of raw material, specifically a DSS for the best use of a given tree stem.

Table 19 Decisions for return processes

Decision type	Decision target	Article	#
Performance Improvement (2)	Resource recovery	Lembersky and Chi (1986) Mangla et al. (2013)	2
Total			2

5.2.6 Non-Specific Decisions

There were 11 papers that made decisions relating to O&SCM that could not be related to any specific SCOR process. These are listed in Table 20.

Table 20 Non-specific decisions

Decision type	Articles	#
Non-specific decisions Broad decision-making process (11)	Zmud (1978), Kirkpatrick and Bell (1989), Vessey (1991), Chau and Bell (1995), Browne et al. (1997), Siskos et al. (1999), Willemain et al. (2003), Jain et al. (2006), Lu and Druzdzel (2009), Huysmans et al. (2011), Wu et al. (2011)	11

Zmud (1978) as well as Vessey (1991) focus on the concept of information and the use of bar charts or tabular/graphical formats to present information in a decision-making process. Kirkpatrick and Bell (1989) survey visual interactive model builders working with decision-making processes. Wu et al. (2011) study the use of cause-effect diagrams to explore decisive factors to adopt decision support software.

A number of empirical researches using experimental methods cover non-specific decisions. For example Huysmans et al. (2011) evaluate the comprehensibility of decision tables, trees and rule-based predictive models. Chau and Bell (1995) carry out an experiment using visual interactive simulation. Browne et al. (1997) experiment using knowledge maps and reasoning-based directed questions with a group of managers. Siskos et al. (1999) explore the use of AI and visual techniques in preference disaggregation analysis. Willemain et al. (2003) conduct an experiment with managers that must cope with flawed DSSs and wrong numbers for an illustrative decision of choosing an optimal location for production. Jain et al. (2006) experiment with a group DM process for multi-criteria decisions. Lu and Druzdzel (2009) focus on the interactive construction of graphical decision models based on causal mechanisms.

5.3 Types of visual analytics

This section focuses on different types of visual analytics identified in the selected body of literature. The approach towards the categories is based on the already presented categorisation discussed in Chapter 2. However, further detail is grounded on the selected literature and created using an iterative cyclical process to achieve the presented categorisation structure. A full list of references against the different types of visual analytics can be seen in the Appendix E.

First, this section explores the thematic findings by the categorisation of different types of visual analytics in the literature, presenting a simple classification structure and frequencies (5.3.1). Second, types of analytics are explored against specific references, classifying their respective fields and associated theory (5.3.2).

5.3.1 Categorisation of different types of visual analytics

First, the identified types of visual analytics are categorised according to their nature: diagrams; interfaces; mapping; modelling, and others, as listed in Table 21 which also lists the frequency of references for the types of visual analytics. From the most referenced to the least referenced are mapping (12), modelling (11) followed by interfaces (9), diagrams (9) and finally graphics (8). The category that falls behind is simulation and statistics with only three references.

Table 21 Categorisation of visual analytics

Category	Types of visual analytics	#
Diagram (9)	Cause and effect diagrams	2
	Decision tables	1
	Decision Trees	3
	Flow diagrams	2
	Inductive System Diagram Technique	1
Graphics (8)	Other Graphics/Plots	7
	Triangle Plots	1
Interfaces (9)	User interface	9
Mapping (12)	Cognitive Mapping	1
	Knowledge Mapping	2
	Layout Mapping	1
	Non-specific Mapping	3
	Process Mapping	2
	Risk Mapping	1
	Strategy Mapping	1
	Value Stream Mapping	1
Modelling (11)	Interpretative Structural Modelling	1
	Object Oriented Modelling	1
	Probabilistic graphical model	1
	VIM	8
Other (3)	PCA	1
	Agent Based simulation	1
	SOM & Clustering	1

Regarding the relative positions of different types of visual analytics and the main categories, mapping is the most represented category which comprehends all efforts of creating a representation of a system, process or idea in a map format, e.g. cognitive mapping by Ackermann and Belton (1994), knowledge mapping by Grabowski and Sanborn (1992) and Browne et al. (1997), layout mapping by Levary and Kalchik (1984), process mapping by Kumar and Arbi (2008) and Völkner and Werners (2000), risk and strategy mapping by Dey (2012), and value stream mapping by Persson (2011).

Modelling, represented by 11 references, is mostly built on VIM, with eight references, (e.g. Bell 1985; Chau and Bell 1995; Hurrion 1985), followed by probability graphical modelling by Wu et al. (2013), object oriented modelling by Biswas and Narahari (2004) and finally interpretative structural modelling Mangla et al. (2013).

The Interfaces category is the third biggest category represented by nine references and it classifies anything that is specifically designed to work as a medium between the machine/system and the user. User interfaces is the biggest type of visual analytics with nine references (e.g. Carravilla and de Sousa 1995; Čižman and Černetič 2004; Cortes et al. 2001; Maliapen and Dangerfield 2010; Özdamar et al. 1998).

The Diagram category is the fourth biggest category with nine references. Cause and effect diagrams are used by Wu et al. (2011) and Dey (2012). Decision tables are used by Huysmans et al. (2011) and decision trees are used by Hess (1993), Dey (2012) and Huysmans et al. (2011). Flow diagrams are used by Hu et al. (2012) and Naruo et al. (1990). Finally, the Inductive System Diagram Technique is exclusive to the work of Burchill and Fine (1997).

The Graphics category is the fifth biggest category with eight references. Triangle plots are only used by Hodgkin et al. (2005) while several other types of diagrams are used in a number of studies such as those by Willemain et al. (2003); Hodgkin et al. (2005); Levary and Kalchik (1984); Lu and Druzdzel (2009); Vessey (1991); Walker (1994); and Zmud (1978).

Finally, the category encompassing simulation and statistics only holds the use of PCA assisted by human cognition, as described by Hodgkin et al. (2005).

Agent-based simulation is described by Hu et al. (2012) and finally the use of self-organising maps and clustering is used by Seret et al. (2012).

5.3.2 Types of analytics, respective fields and theories

Table 22 compares the main underlying theory identified in the paper with the respective field of analytical tools used, while Table 23 lists different types of analytics which are sometimes repeated in different fields and across different theories; this explains why 41 articles provide a total of 65 co-observations based on the frequency of types of analytics used and not the references. The main theories identified are control theory (25), decision theory (19), systems theory (19) and finally network theory (2). After analysing the tables, a pattern between theoretical fields and fields of analytics arises. For example, control theory is highly correlated with process control (16) and human-computer interaction (9). Decision theory is the highest correlation point with decision analysis (18) and with expert systems (1). Systems theory is related to simulation (11), systems design (4), and human-computer interaction (4). Network theory is the least represented, related only to Baysian networks (1) and expert systems (1). These data show that control theory is used in situations where the managerial challenge is to control processes, and similarly for the remaining 'hot-spots' decision theory for decision analysis and systems theory for simulation applications.

Table 22 Theory as against fields of analytics

Theory \ Field of analytics	Bayesian networks	Decision Analysis	Expert Systems	Human-Computer Interaction	Knowledge Discovery	Process Control	Simulation	System design	Grand Total
Control Theory				**9**		**16**			**25**
Decision Theory		**18**	1						**19**
Network Theory	1				1				**2**
System Theory				4			**11**	4	**19**
Grand Total	**1**	**18**	**1**	**13**	**1**	**16**	**11**	**4**	**65**

Control theory deals with mathematics and engineering to deal with the dynamic system's behaviour that is mostly based on input-output models. Decision theory spans fields such as mathematics, statistics, psychology, economics and even philosophy, and it is focused on identifying uncertainties and values related to decisions, rationality and optimal decisions, being often related to game theory and economic agent interaction. Network Theory belongs to computer science, graph theory and network science, being concerned with the study of graphs as a representation of relations between discrete objects. System theory focuses on systems and system thinking, concerned with finding principles that can be used to successfully deploy and manage systems.

Table 23 Fields of analytics against types of analytics

Field of analytics / Types of analytics	Bayesian networks	Decision Analysis	Expert Systems	Human-Computer Interaction	Knowledge Discovery	Process Control	Simulation	System design	Grand Total
Agent Based simulation				1			1		2
Cause and effect diagrams		2							2
Decision tables		1							1
Decision Trees		3							3
Flow diagrams				1		1	1		3
Graphics		5				1		1	7
Inductive System Diagram Technique						1			1
Interpretative Structural Modelling								1	1
Mapping		6	1	2		5	1		15
Object Oriented Modelling							1		1
PCA								1	1
Probabilistic graphical model	1								1
SOM & Clustering					1				1
User interface				9		8	1		18
VIM		1					6	1	8
Grand Total	1	18	1	13	1	16	11	4	65

5.4 Impact of visual analytics

This section presents the thematic analysis regarding the impact of visual analytics described in the selected literature as listed in Table 24.

From a broad perspective, as listed in Table 24, most of the selected papers identify a positive impact (36 papers) while the remaining consider it to be neutral (5 papers). The second most common theme identified is better understanding of the problem under scrutiny as it is mentioned in 24 contributions. Finally, the third most common impact of visual analytics is that it promotes managers' involvement in the decision-making process, identified by 11 contributions. The remaining impacts are regarding speed improvement (8 references), better communication (7 references), higher efficiency and ease (5 references each), man plus machine integration (4 references), power of visuals promoting ideas and finally trust in data analysis (2 references each). Each specific reference to authors and impact can be seen in Table 24 but was not included in the text due to space considerations.

Regarding the specifics of each identified impact, Positive Impact is a ‘good’ effect on the decision-making process or a ‘good’ outcome for the managerial challenge that authors were set to solve. Better Understanding is the effect of making the problem and parameters clear for managers, e.g. pattern uncovering and trend discovery. Management Involvement is the effect of involving managers in the decision-making process, e.g. a more engaging process. Speed is a quicker decision-making process or problem solving. Better Communication is when the decision-making process is easier to communicate between decision-makers. Efficiency is when the process is done effectively and with fewer resources. Neutral Impact is when the application of some specific type of analytic presents no significant difference between with or without that type of analytic. Ease is the effect of making something easier, in this case the decision-making process. The ‘Man + Machine’ effect is the power to bridge the gap between IT and the managers, i.e. effective interface. Power of Visuals is mostly to do with the buy-in from management to realise the advantage of visual representations. Trust is the effect of believing in the reliability and accuracy of the analysis, overcoming the “black-box” effect (Fawcett, S.E., Fawcett, A.M., Watson, B.J., Magnan 2012). Groups is the effect of improving team-work decisions. Data Quality is the effect of improving the reliability and accuracy of data. Alignment is the effect that enables better management through common goal setting or better understanding of the aims, so the decision-processes can be directed towards a common goal. Less Information Overload is the effect of relieving the manager from overwhelming quantities of information that are likely to cause a negative effect on the decision-making process because human ability to process data and information is limited. Productivity is the effect of doing more with the same. Flexibility is the effect of working within a varied set of conditions while maintaining effectiveness. Misinterpretation is the negative effect of misunderstanding something, e.g. the analysis that is confusing leads to misinterpretation and wrong decisions. Real-time Management is the effect of driving quicker, more reactive and agile management.

Although higher level aggregation between effects is possible, this granularity brings depth to different contributions by highlighting some of the particularities exclusive to some papers. For example, although efficiency is similar to productivity, Levary and Kalchik (1984) discuss very different impacts on the DM process from, for example, Naruo et al. (1990). The first present a group decision-making process supported by visual analytics while the second develops a knowledge-based DSS to diagnose malfunctions of production equipment with speed of focus.

Table 24 Impact of analytics per article

Article \ Impact	Positive Impact	Better Understanding	Management Involvement	Speed	Better Communication	Efficiency	Neutral Impact	Ease	Man + Machine	Power of Visuals	Trust	Groups	Data Quality	Alignment	Less Information Overload	Productivity	Flexibility	Misinterpretation	Real-time Management
Zmud (1978)							✓												
Levary and Kalchik (1984)	✓															✓			
Hurrion (1985)	✓				✓						✓								
Bell (1985)	✓	✓	✓								✓								
Lembersky and Chi (1986)	✓	✓	✓					✓											
Day et al. (1987)	✓	✓																	
Kirkpatrick and Bell (1989)	✓		✓	✓	✓														
Naruo et al. (1990)	✓			✓		✓													
Vessey (1991)				✓			✓	✓											
New et al. (1991)	✓				✓													✓	
Grabowski and Sanborn (1992)	✓	✓		✓											✓				
Hess (1993)	✓	✓	✓																
Walker (1994)	✓			✓						✓			✓						
Ackermann and Belton (1994)	✓	✓										✓							
Chau and Bell (1995)	✓								✓	✓									
Carravilla and de Sousa (1995)	✓		✓																
Burchill and Fine (1997)	✓	✓																	
Browne et al. (1997)	✓		✓																
Özdamar et al. (1998)	✓	✓	✓					✓											
Siskos et al. (1999)	✓	✓	✓						✓										
Völkner and Werners (2000)	✓	✓																	
Cortes et al. (2001)	✓	✓															✓		
Willemain et al. (2003)							✓		✓										
Čižman and Černetič (2004)	✓	✓	✓					✓											
Biswas and Narahari (2004)	✓	✓																	
Hodgkin et al. (2005)	✓	✓		✓															
Jain et al. (2006)		✓		✓	✓		✓												
Pal and Kumar (2008)	✓		✓	✓				✓											
Kumar and Arbi (2008)	✓					✓													
Lu and Druzdzel (2009)	✓	✓							✓										
Maliapen and Dangerfield (2010)	✓	✓	✓			✓													
Wu et al. (2011)	✓	✓			✓														
Persson (2011)	✓	✓																	
Huysmans et al. (2011)							✓												
Cottyn et al. (2011)	✓	✓												✓					✓
Seret et al. (2012)	✓	✓																	
Kayis and Karningsih (2012)	✓				✓														
Hu et al. (2012)	✓	✓																	
Dey (2012)	✓					✓													
Wu et al. (2013)	✓	✓			✓														
Mangla et al. (2013)	✓	✓				✓													
Total	**36**	**24**	**11**	**8**	**7**	**5**	**5**	**5**	**4**	**2**	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

5.5 Conclusion

This section concludes Chapter 5 which summarises the main themes covered by the selected body of literature by presenting the categorisation and respective literature. Following the review questions three main sections are covered. Firstly the focus falls on different types of decisions in the O&SCM context, followed by the identification and categorisation of visual analytics discussed in each paper, and ending with the analysis of the impact of visual analytics identified in each contribution. Each of the sections analyses the literature against a grounded category list, and its main purpose is to present emergent themes from the selected body of literature that is relevant to the review questions and prepare a cross-thematic analysis for Chapter 6.

The most represented themes in the decision area are the Plan processes (16 references) and Make processes (14 references) and the most dominant sub-classification of the decisions is in both references focused on performance improvement.

The most cited visual analytics can be categorised as being mapping, modelling and interfaces with 12, 11, and 10 references respectively. In more detail, User Interfaces with nine references as well as VIM with eight references are the most cited types of visual analytics.

The three most frequent impact dimensions identified in the selected body of literature were (from the highest to lowest) a positive impact without specificity, followed by a better understanding of the process/problem and finally management involvement in the decision-making process. Not as frequent, but still important, dimensions are also identified in the selected literature, for example: Speed; Better communication; Efficiency; Ease; and Trust.

6 Cross-Thematic Analysis – Answering the review questions

"Knowledge discovery holds the promise of insight into large, otherwise opaque datasets. (…) current [data] analysis techniques are inefficient; as they fail to directly embed the user in dataset exploration and a better solution involves the user and algorithm being more tightly coupled." (Hutchison and Mitchell 2008, p.v)

6.1 Introduction

After this introduction, Chapter 6 focuses on answering the review questions identified in Chapter 2 by cross-comparing and discussing the previously identified themes in Chapter 5.

This section presents a cross-thematic analysis of the three main thematic blocks which are directly related to the review questions of this SLR. Firstly the interest is to identify the **different types of visual analytics** present in literature; secondly, **what O&SCM decisions do they support**; and thirdly, what is **the impact of these visual analytics**.

So far the SLR has identified different types of visual analytics, a number of O&SCM decisions as well as the impact described in the literature on the managerial problem or DM process. These three segments are aligned with the three segments related to the three review questions of this SLR. Firstly, 6.2 breaks down decisions, besides the "non-specific" decisions, into the SCOR reference model processes: Source; Make; Deliver; Return; and Plan. Secondly, 6.3 presents the different types of visual analytics and their respective impacts.

Chapter 6 is composed of five main sections, as illustrated in Figure 18. 6.2 gives the relation between different types of analytics and the respective O&SCM decisions. 6.3 presents the discussion of different types of visual analytics and their respective impacts. 6.4 presents a model based on the conceptual findings and cross-thematic analysis. 6.5 specifically answers the review questions of this SLR.

6.2 Visual Analytics vs. O&SCM decisions analysis

- 6.2.1 Plan decisions vs. visual analytics
- 6.2.2 Source decisions vs. visual analytics
- 6.2.3 Make decisions vs. visual analytics
- 6.2.4 Deliver decisions vs. visual analytics
- 6.2.5 Return decisions vs. visual analytics
- 6.2.6 Non-Specific decisions vs. visual analytics

6.3 Type of visual analytics vs. impact analysis

6.4 Conceptual model

6.5 Answering the review questions

6.6 Conclusion

Figure 18 Cross-Thematic Analysis chapter structure

Firstly, different types of previously identified visual analytics are connected with the respective O&SCM decisions that they support in the selected body of literature; 6.2 breaks the decisions down into the SCOR reference model processes: Source; Make; Deliver; Return; Plan and the “non-specific” decisions. Secondly, 6.3 compares and discusses the different types of visual analytics regarding the respective impact.

6.5s, sums up the three themes into an overview, discussing the dominant types of analytics, the decisions that they support and the respective impact of analytics, which together answer the three review questions of this SLR.

6.2 Visual Analytics vs. O&SCM decisions analysis

This section focuses on the cross analysis between the different types of visual analytics and the respective decisions in the O&SCM context. The main objective of this section is to identify the most dominant associations between types of decisions and types of analytics used to support them.

Table 25 presents an overview of the frequency between visual analytics types and SCOR reference model categories. Although 'plan type' decisions were the most represented in the literature, specifically 16 references focused on plan against 13 focused on make, the higher number of different visual analytics is used for 'make type' decisions with 21 communalities (same papers apply multiple methods). The most frequent combinations between decisions for make processes are with mapping and diagrams (6 communalities each). For planning, the most used types of analytics are modelling (6 communalities), followed by graphical user interfaces (GUIs) and mapping (4 communalities each). For non-specific decisions, the most common type of visual analytics is the use of graphics with 4 communalities (e.g. Vessey 1991; Zmud 1978).

Table 25 Visual analytics against SCOR reference model overview

SCOR Reference process / Types of Analytics type	Plan	Source	Make	Deliver	Return	Non Specific	Total
Diagram			6			3	9
Graphics	2		3			4	9
GUI	4	1	3	2		1	11
Mapping	4	1	6	1	1	1	14
Modelling	6		2	3	2	3	16
Simulation			1				1
Statistics	1			1			2
Total	17	2	21	7	3	12	62

In detail, make processes are commonly analysed in schematic form by looking at the structure of processes, i.e. by understanding as it is. Consequently, process mapping (e.g. Grabowski and Sanborn 1992; Hu et al. 2012) as well as extensive use of diagrams (e.g. Burchill and Fine 1997; Dey 2012) are fairly common and well suited for the purpose. On the other hand, planning mostly benefits from insight into future and process monitoring, what justifies the extensive use of modelling (e.g. Biswas and Narahari 2004; Hodgkin et al. 2005), mapping (e.g. Ackermann and Belton 1994; Day et al. 1987) and graphical user interfaces (e.g. Cortes et al. 2001; Maliapen and Dangerfield 2010). Both modelling and mapping aim at representing a system from a specific perspective which eventually results in a better understanding of different elements and the relations between them, while graphical user interfaces enable the communication of information in real-time for decision-making processes which is necessary for efficient planning.

Regarding the non-specific decisions, most of the literature that focuses on the process of decision-making itself, and not some specific decision, mostly analyses the impact of visual representations of data to improve the DM process, which justifies the high communalities with graphics, diagrams and visual modelling.

The following sections expand Table 25 through each category of decision type according to the SCOR reference process: 6.2.1 details authors focused on different types of analytics used for plan processes; 6.2.2 for source decisions; 6.2.3 for make processes; 6.2.4 for deliver processes; 6.2.5 for return processes; and finally, 6.2.6 for non-specific decisions. An expanded table with references mapped against the intersection between types of decisions and types of visual analytics can be seen in the Appendix D.

6.2.1 Plan decisions vs. visual analytics

Plan decisions are one of the most represented types of decisions in this SLR. For inventory management, specifically inventory policy optimisation decisions, Biswas and Narahari (2004) use object oriented modelling. For layout definition in a group DM process, Levary and Kalchik (1984) use graphical representations and layout mapping. For performance improvement, Kumar and Arbi (2008) use process mapping to decide on outsourcing strategies. For process optimisation Völkner and Werners (2000) use process mapping. For process planning, Hodgkin et al. (2005) use triangle plots, VIM and PCA while Maliapen and Dangerfield (2010) rely on a data-rich user interface. For SC redesign, Persson (2011) uses value stream mapping. For production planning decisions, namely manufacturing capacity planning, New et al. (1991) use VIM as do Bell (1985) and Hurrion (1985) who apply it to production and delivery planning, specifically delivery plan optimisation. For resource allocation decisions, Wu et al. (2013) use a probabilistic graphical model for manufacturing resource allocation and Cortes et al. (2001) employ user interfaces for supply network optimisation. For strategic planning, Day et al. (1987) use strategy mapping for competitive analysis and Ackermann and Belton (1994) use cognitive mapping for group-strategy development.

6.2.2 Source decisions vs. visual analytics

For source decisions two major categories apply: risk management and supplier management. For the former, Kayis and Karningsih (2012) use mapping to support source and make strategy selection, while for the latter, Pal and Kumar (2008) rely on a user interface to support managers in vendor evaluation and selection.

6.2.3 Make decisions vs. visual analytics

For make decisions a relatively large number of contributions apply a number of different analytic types for different decisions.

For equipment maintenance, Naruo et al. (1990) use flow diagrams and Walker (1994) uses rich graphic representations, for machine replacement decisions. For inventory management, Čižman and Černetič (2004) rely on user interfaces for stock reduction decisions. For layout definition, Levary and Kalchik (1984) apply both graphical representations as well as layout mapping processes. For manufacturing, specifically product development, Burchill and Fine (1997) rely on an inductive system diagram technique. For performance improvement, Hu et al. (2012) use flow diagrams, user interfaces and mapping for business engineering alignment decisions. For manufacturing processes and objectives alignment Cottyn et al. (2011) use mixed mapping. Finally, in the performance improvement decision category, Lembersky and Chi (1986) use VIM for resource recovery decisions. For piloting decisions, specifically real-time shipboard piloting, Grabowski and Sanborn (1992) use both user interfaces and knowledge mapping. For production planning, specifically production optimisation, Hurrion (1985) relies on VIM. For project selection and specifically group project selection, Hess (1993) uses decision trees. For risk management, specifically risk mitigation strategy decisions, Dey (2012) uses cause and effect diagrams, decision trees and mapping. Finally, for source and make strategy selection Kayis and Karningsih (2012) use mapping.

6.2.4 Deliver decisions vs. visual analytics

Regarding decisions focused on deliver processes, for inventory management, specifically inventory policy optimisation, Biswas and Narahari (2004) use object oriented modelling and for stock reduction Čižman and Černetič (2004) set up a user interface. For direct marketing Seret et al. (2012) use self-organising maps and clustering of clients. For performance improvement, specifically delivery process planning, Maliapen and Dangerfield (2010) use a tailored user interface. For delivery planning, specifically optimisation decisions, Bell (1985) and Hurrion (1985) use VIM.

6.2.5 Return decisions vs. visual analytics

Return decisions are mostly focused on performance improvement, specifically resource recovery decisions. The only two contributions focused on this types of decisions use modelling, where Mangla et al. (2013) use interpretative structural modelling and Lembersky and Chi (1986) use VIM.

6.2.6 Non-Specific decisions vs. visual analytics

For non-specific decisions, most of the literature is experimental, focusing on the broad decision-making process. Graphics and plots are the most significant methods used in studies by Zmud (1978), Vessey (1991), Willemain et al. (2003), and Lu and Druzdzel (2009). VIM is used by Kirkpatrick and Bell (1989), Chau and Bell (1995) and Jain et al. (2006). In the diagram category, cause and effect diagrams are used by Wu et al. (2011), and decision tables and decision trees by Huysmans et al. (2011). User interface is applied by Siskos et al. (1999), and knowledge mapping by Browne et al. (1997).

6.3 Type of visual analytics vs. impact analysis

This section compares the identified types of visual analytics against the impact described in the literature regarding the problem that has been set to address. Table 26 lists the cross-comparison which counts the frequency of communalities referenced in the selected body of literature. For example, Bell (1985) discusses VIM as an OR technique, identifying several implications such as a strong positive impact on management, better understanding, management involvement and trust. This gives the cross-comparison between VIM and the impact categories a point for each of the references mentioning it.

One of the most striking outliers regarding the analytics categories and specifically different types is the dimension of “interactivity” highlighted by the positive impact reported by the use of GUIs as well as VIM. Besides the positive impact, interactivity (represented by GUIs and VIM) is highly associated with a better understanding of the decision-making process, management involvement, speed and better communication. This drives trust in the analysis which is the case with VIM. The positive impact of interactive analytics on management, specifically DM processes, might be related to the Hawthorne Effect (Franke and Kaul 1978; McCarney et al. 2007; Parsons 1978; Wickstrom and Bendix 2000). This effect improves the user’s confidence in, and ownership of, the results produced by the analytic process or tool due to the high degree of involvement/interactivity.

The hotspots in better understanding, management involvement and better communication, support the idea that “seeing” may be believing or disbelieving analysis as well as the power of an interactive visual representation in facilitating the analytical thought processes.

Table 26 Visual analytics vs. impact for decision-making processes

Analytics category	Diagram (19)					Graphics (18)		GUI (31)	Mapping (29)								Modelling (36)				Simulation (2)	Statistics (5)		
Analytics type / Impact	Cause and effect diagrams	Decision tables	Decision Trees	Flow diagrams	Inductive System Diagram Technique	Plots	Triangle Plots	User interface	Cognitive Mapping	Knowledge Mapping	Layout Mapping	Mapping	Process Mapping	Risk Mapping	Strategy Mapping	Value Stream Mapping	Interpretative Structural Modelling	Object Oriented Modelling	Probabilistic graphical model	VIM	Agent Based simulation	SOM & Clustering	PCA	Total
Positive Impact	2		2	2	1	3	1	9	1	2	1	3	2	1	1	1	1	1	1	7	1	1	1	45
Better Understanding	1		1	1	1	1	1	7	1	1		2	1		1	1	1	1	1	4	1	1	1	30
Management Involvement			1					6		1										3				11
Speed				1		2	1	2		1										3			1	11
Better Communication	1											1							1	4				7
Efficiency	1		1	1				1					1	1			1							7
Neutral Impact		1	1			3														1				6
Ease						1		3												1				5
Man + Machine						2		1												1				4
Power of visuals						1														1				2
Trust																				2				2
Group integration									1															1
Data quality						1																		1
Alignment												1												1
Less information overload								1		1														2
Productivity						1					1													2
Flexibility								1																1
Misinterpretation																				1				1
Real-time management												1												1
Total	5	1	6	5	2	15	3	31	3	6	2	8	4	2	2	2	3	2	3	28	2	2	3	140

Section 6.4 focuses on the overall conceptual model derived from the cross-thematic analysis. The target is to set up a model that would support the answers to the review questions of this SLR, i.e. an overview of different types of analytics, which decisions they support and finally what is the impact of their application.

6.4 Conceptual model

The previously identified relations enable the development of a conceptual model structuring different types of visual analytics against O&SCM decision types and respective impacts. The most basic relational model between the three themes is illustrated in Figure 19 and further detailed in Figure 20.

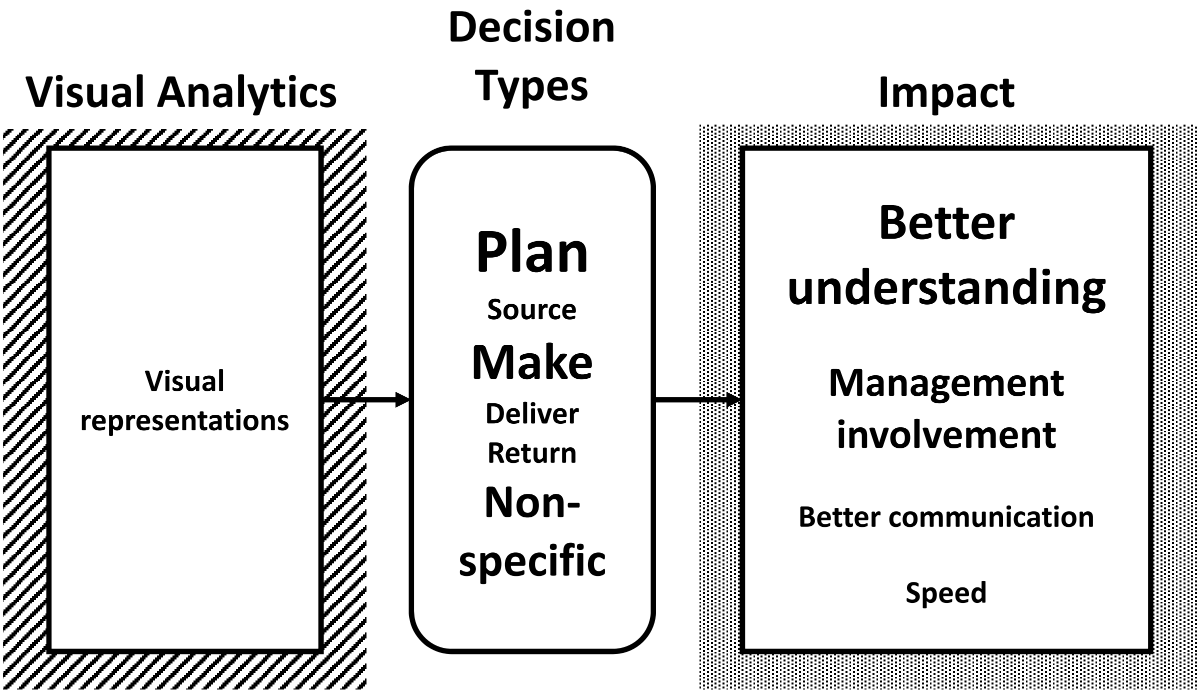

Figure 19 Basic conceptual model

The most basic relationship between visual analytics, decision types and their consequent impact is linear, as illustrated in Figure 19. Visual analytics support decision processes in the O&SCM context, mostly enabling a better understanding of the problems to be solved, and better management involvement and communication, while sometimes improving the speed of the process.

Figure 20 represents a more detailed conceptual model of this SLR. It uses the same three groups of elements under analysis: visual analytics; decision types; and impact. One paper can have multiple decision types and multiple visual analytics types and each can have multiple impacts. This explains why the totals of each group are higher than the total number of articles under review (41 articles) as the relationship between the number of papers and each theme is not one to one.

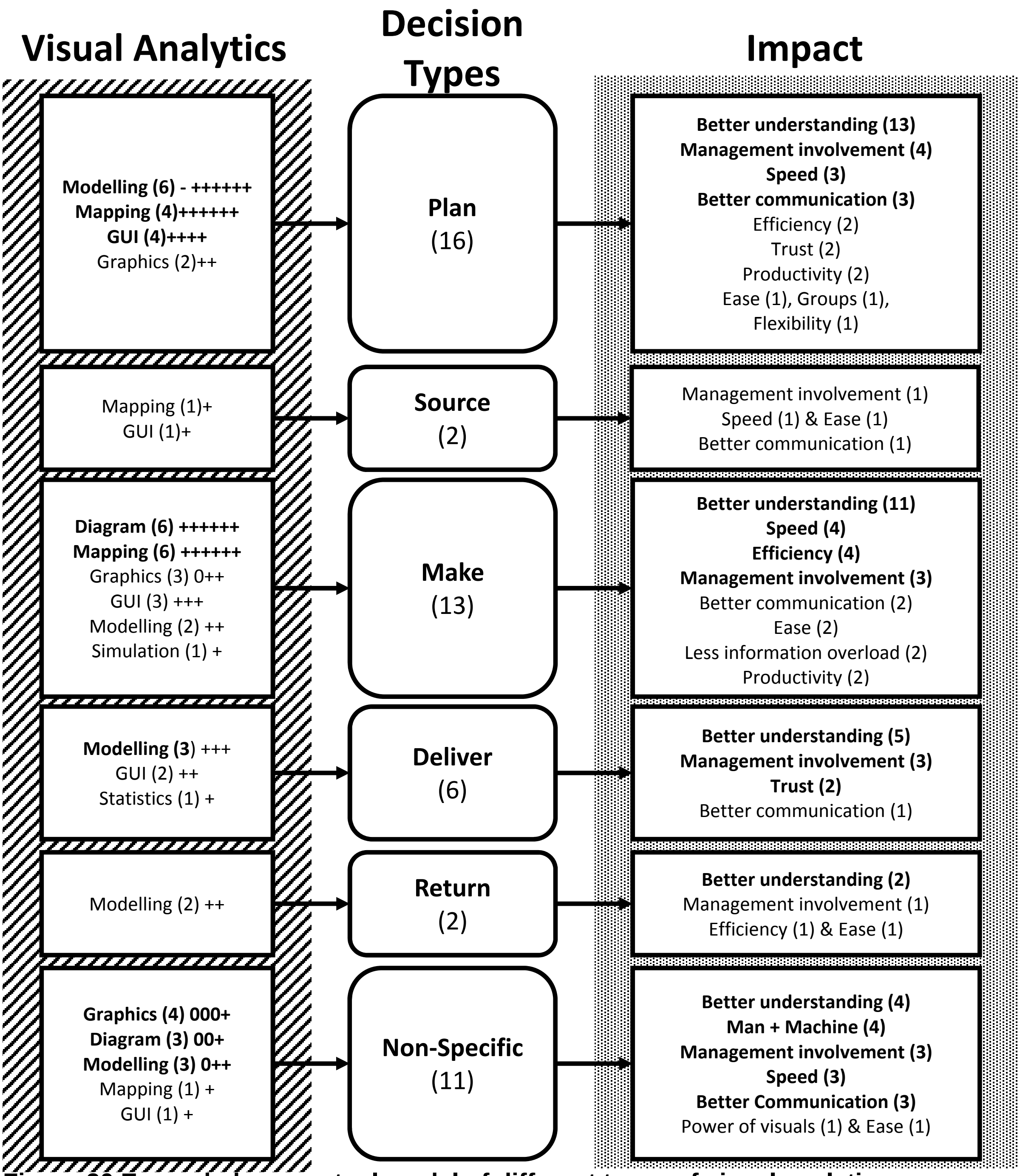

Figure 20 Expanded conceptual model of different types of visual analytics

Additionally, each list is organised from the most frequent to the least frequent, which means that the first items in each square box are the most relevant ones for the purpose of extracting an overall model regarding the use of visual analytics to support DM processes in an O&SCM context. In the visual analytics area, the number next to the analytics type indicates the frequency for that specific decision type, followed by the impact quality ('-' stands for negative; '0' for neutral; and '+' for positive).

For example, out of 16 papers, the most used visual analytics type is modelling with six references focused on decisions regarding plan decision type, where six authors point out the positive impact of modelling while one mentions a negative aspect as well, specifically the possibility of mis-interpretation of the models (New et al. 1991). Similarly other types of visual analytics match 'plan type' decisions, such as mapping (4), graphical user interfaces (4) and graphics (2), which are used as well and are all considered positive for the DM process. The consequent impact of the respective set of visual analytics is mostly better understanding (13 references), better management involvement (4), quicker decisions (speed with three references) and better communication (three references).

The trend visible in Figure 20 shows some overall communalities as well as particular associations. Regarding communalities, modelling, diagrams and graphics are the most common types of visual analytics applied in the DM processes. The most common consequence or impact of their application is a better understanding of the problem which is the top impact besides the overall positive effect of applying visual support.

Further development in terms of particularities answers the review questions of this SLR and this is explained in 6.5.

6.5 Answering the review questions

This review was structured according to the review questions identified in Chapter 2 Positioning the Field of Inquiry:

What types of visual analytics are used to support DM in O&SCM?

There are three sub questions:

1. What types of visual analytics are used?
2. What O&SCM decisions do they support?
3. What impact do they have on the DM process and outcome?

Regarding these three review questions, the answer that follow are structured using the SCOR reference model. To enable better plan decisions, as plan processes balance demand and supply to develop a course of action which best meets sourcing, production and delivery requirements, the matching types of analytics described in the literature are modelling, mapping and interfaces between data and managers. These types of analytics lead management to a better understanding of the problems, and a consequent better involvement of different decision makers, with quicker decision processes and easier communication.

Decisions focused on the make processes are some of the best represented in this SLR. Mapping of different types, diagrams and forms of representation of processes are the most used visual tool to support management which achieves a better view of the problem, which also increases productivity, speed and efficiency.

Deliver processes are one of the under-represented groups of decisions. These are mostly supported by modelling and graphical user interfaces which provide better understanding of the problem and management involvement into the process, improving the trust in data/analysis.

Decisions regarding source or return processes are not as common in the selected body of literature and nothing stands out clearly from only two references. Those, however, apply similar types of analytics (mapping and GUIs for source and modelling for return) and the outcomes are coherent (e.g. Management involvement, better understanding).

Finally, regarding the particularities of the non-specific decisions, the set of visual analytics supporting the DM processes in general are graphics, diagrams and modelling. One interesting particularity of this decision type is the fact that a number of contributions classify the impact of visual representations as neutral (Vessey 1991; Willemain et al. 2003; Zmud 1978). For example, one experiment focused specifically on whether visual representations help to overcome flawed DSSs or ‘bad numbers’ (Willemain et al. 2003); the results showed that people supported by visuals did not made significantly better decisions alone than those that were not. Instead, the human cognitive ability was the differentiator. This supports the saying that “a fool with a tool is still a fool”.

Overall, the emerging idea through the use of graphical user interfaces is that visual analytics enable interactivity between the decision maker and the system. This is in accordance with the claim that the interactive paradigm of mining and visualisation as two separate steps must be replaced by the data mining equivalent of direct manipulation (Ceglar and Roddick 2007).

6.6 Conclusion

This section concludes the cross-thematic analysis and answers the review questions using outputs from chapter 5. The main types of visual analytics are modelling, diagrams and graphics which are mostly applied to make and plan decisions with positive effect, improving understanding, easing the DM process and enabling better management involvement in it.

The impact of analytics and the different types of analytics are in accordance with the literature, such as the effect of improving the analysis outputs using the Hawthorne Effect (McCarney et al. 2007) through the interactive nature of visual analytics. Additionally, the findings support the latest claims regarding the need to change the paradigm about the separation between analysis and visualisation into direct manipulation (Ceglar and Roddick 2007) enabled by graphical user interfaces. Finally, all three review questions are answered after the conceptual model, which provides an overview for the three thematic building blocks for the respective three review questions and the relationship in between. Further, chapter 7 concludes this SLR by reviewing the research objectives, contribution to knowledge, critique, personal learning and finally an overall summary.

7 Conclusion

"Visual data mining exploits the human perceptual faculties to detect interesting relationships in the data. To support the detection of relationships it is important to visualize data in a form that is easy understandable to humans." (Hutchison and Mitchell 2008, p.91)

7.1 Introduction

The final chapter as illustrated in Figure 21 is based on four main parts: Review against research objectives, contribution to knowledge, critique and personal learning. 7.2 focuses on reviewing this SLR against the research objectives. 7.3 focuses on the contribution to knowledge breaking into two sections. 7.3.1 presents the implications for theory and 7.3.2 the implications for practice. 7.4 concerns the critique of this SLR, in which 7.4.1 highlights the strengths of this SLR, 7.4.2 presents its limitations and 7.4.3 presents suggestions for further research. 7.5 focuses on my personal learning broken down into three main sections. First 7.5.1 discusses my knowledge about the review questions, and 7.5.2 summarises the development of my research skills. Finally, 7.6 provides an overall summary closing this thesis.

7.2 Review against research objectives

7.3 Contribution to knowledge
- 7.3.1 Implications for theory
- 7.3.2 Implications for practice

7.4 Critique
- 7.4.1 Strengths
- 7.4.2 Limitations
- 7.4.3 Further research

7.5 Personal learning
- 7.5.1 Knowledge about the review question
- 7.5.2 Development of research skills

7.6 Overall summary

Figure 21 Conclusion chapter structure

7.2 Review against research objectives

The research objective of this SLR is to apply an SLR methodology to answer the following review questions:

What types of visual analytics are used to support DM in O&SCM?

There are three sub questions:

1. What types of visual analytics are used?
2. What O&SCM decisions do they support?
3. What impact do they have on the DM process and outcome?

This SLR is highly dependent on the methodology used, specifically the SLR process which is a methodology to review literature, while minimising bias, and arrive objectively at a research gap or pertinent research question for further research (Tranfield et al. 2003). The methodological objective was met to the extent that this SLR is based on an explicit protocol in accordance with the SLR process and reviewed by specialists in that process.

From the subject side, the theme of visual analytics is novel. There are not many papers referring to it explicitly and the first reference to the term visual analytics can be found in 2008 (Keim et al. 2008). Consequently, this SLR met the challenge of identifying different types of visual analytics in a specific context. Examples of visual analytics are graphical representations, models, diagrams and graphical user interfaces. These had to have a specific purpose which was to support a decision process in an O&SCM context. Consequently, the selected literature is empirical, exception for a literature review by Vessey (1991). The different decisions types were discussed and organised under the SCOR reference model, a recognised standard in the operations field. Most of the contributions focused on ‘plan type’ decisions as well as ‘make type’. Along with the application and discussion of tools for some given managerial challenges, the literature referred to consequent implications and impact. Most of the authors identified the use of visual analytics as being positive as well as improving the understanding of the problem (e.g. data, limitations, relationships between objects). Along with a better understanding of the problem, visual analytics enabled better communication, efficiency and management involvement into the process.

The three elements (types, decisions and impact) are expanded throughout the body of this SLR, specifically in Chapter 5, then cross-analysed and turned into a conceptual model in Chapter 6. This holds the answer to the review questions. Therefore, this SLR meets both the methodological and thematic objectives by following a review through a protocol and providing answers to the review questions at the end.

7.3 Contribution to knowledge

7.3.1 Implications for theory

The main contribution to theory is that at the moment this is likely to be the first SLR focused on the use of visual analytics in an O&SCM context. Consequently it supports further research in the field by providing a solid and systematic literature grounding on this specific topic.

The fields that integrate the rising theme of visual analytics are many, such as visual perception, information and scientific data visualisation, cognitive psychology, design computing, computer graphics, and data mining and multimedia. Consequently there is a need to build frameworks that would integrate the entire legacy and enable the development of the field of visual analytics. By identifying some of the underlying theories and connecting them to the tools is a step forward to create a more solid theoretical basis and further exploration.

This SLR shows the lack of research focused on visual analytics and how it impacts the DM processes. Many of the contributions are outdated and do not account for the latest technological development as can be observed in Chapter 4. Since this field is strongly dependent on technology and IT capabilities, this SLR provides evidence of the existing gap in the literature regarding this nascent field.

7.3.2 Implications for practice

The use of visual analytics has been described in the literature over recent decades to a certain extent. This SLR provides a conceptual model that can improve the practical applications of visual analytics projects by providing a theoretical basis and a set of visual analytics types, where they are applicable and their consequent impact, as described in previous empirical research.

7.4 Critique

7.4.1 Strengths

The strongest pattern found was mostly related to the interactivity between data or a system and the decision maker, and associated with several positive impacts. This is in accordance with the idea of interactivity. Both from the behavioural side Hawthorne Effect (Franke and Kaul 1978; McCarney et al. 2007; Parsons 1978; Wickstrom and Bendix 2000). This effect improves the user's confidence in, and ownership of, the results produced by the analytic process or tool due to the high degree of involvement/interactivity. Additionally, the findings of this SLR regarding the types of analytics focused on interactivity are in accordance with the necessary changes in paradigm identified by Celgar and Roddick (2007) who claim that the interactive paradigm of data mining and visualisation as separate must be replaced by direct manipulation.

Additionally, SLRs are valuable literature grounds for further empirical research as this SLR in particular identifies the lack of recent contributions focused on the use of visual analytics to support DM in practice in the O&SCM context.

7.4.2 Limitations

This section focuses on the limitations of this SLR. The main limitation is regarding the lack of a formal definition of the term "visual analytics" (Davenport 2006; Liberatore and Luo 2010; Marchand and Peppard 2013). Another limitation is the final paper selection choices and bias.

Without a formal definition of the term "visual analytics" and its relative embryonic state as a research field (Hutchison and Mitchell 2008; Keim et al.

2008) it was necessary to make a number of assumptions about what constitutes visual analytics and project them into the previously published literature that never specifically mentions this term.

Regarding the final paper selection choices and biases, subjective personal choices made during the SLR process, specifically the inclusion/exclusion criteria assessment as well as quality appraisal, is purely based on my own judgement and limited experience as a researcher.

Another limitation is the apparent bias found in the literature regarding the quality of the impact of proposed new methods in the empirical literature. Naturally with the empirical literature presenting case-based research, applying new tools are positively biased, tending to present a positive impact while papers researching the impact of visual support often showed a neutral impact of visual support. This can consequently distort the findings regarding the impact of the different types of analytics present in this SLR.

7.4.3 Further research

Further empirical research on the use of visual analytics for DM processes in the O&SCM context is required, since there is a scarcity of literature specifically focused on the subject.

The term itself requires more formal definition since its first use can be tracked back only to 2008 (Keim et al. 2008).

Additionally, the problem of quantifying the benefits of visual analytics must be addressed. This SLR identifies some of the impacts, most of them benefits. However, highly interactive methods can be more time-consuming to develop and it is critical to find ways to show clear time improvement or quality improvement over non-visual analytics.

Finally, human beings have a unique cognitive ability and contextual awareness which, if merged with the increasing IT capability to handle large amounts of data, turn visual analytics into a promising field that must be researched further due to the constant parallel IT progress.

7.5 Personal learning

This specific SLR experience provided me with a unique perspective over literature which I am likely never to have had if this SLR had been optional. There are two main points regarding my personal learning: firstly the knowledge gained about the use of visual analytics in an O&SCM DM context; and secondly, the development of my research skills.

7.5.1 Knowledge about the review questions

In order to identify visual analytics without any paper prior to 2008 mentioning the term, I had to make several assumptions and learned a number of different methods and tools that could go under the umbrella of this new term. The SLR exercise was mostly useful to pinpoint prior empirical knowledge and general culture with academic literature about it.

7.5.2 Development of research skills

As a researcher I learned to go through literature en masse trying to keep a minimum degree of attention and criticality. I believe I found some endurance to survive the less interesting tasks. Fighting boredom and anxiety management was certainly one of the main skills that I obtained through conducting the SLR. It was also a moment of self-discovery as I find a plethora of interesting things to do besides concentrating on the SLR during the months of writing.

Another important learning point was to obtain better training with referencing software, to read articles quickly and cover their main points, to focus on what I was specifically looking for and not everything that is interesting in the paper but outside the SLR scope. A precious piece of learning was to gain different points of view on the same body of literature from different levels of abstraction.

Finally, due to the low level of enjoyment I endured in conducting this SLR, it has made me go through long introspective moments of “what I am doing here” and considering if the PhD journey is suitable for me and my style of work after having formerly had an engineering background.

7.6 Overall summary

This section brings this SLR to a conclusion. After presenting the managerial challenge in chapter 1, the problem is positioned in the field in chapter 2 which concludes with the research objectives and SLR questions. Chapter 3 presents the methodology and the SLR protocol. Chapter 4 describes the selected body of literature regarding a number of attributes such as, for example year or type of publication. Chapter 5 dives into the paper contents and presents the three main thematic segments according to the review questions, namely the types of visual analytics, types of decisions and impacts/practical implications. Chapter 6 analyses the themes found in chapter 5, presenting the main relations between those themes and closing with a conceptual model which answers the review questions. Chapter 7 concludes the SLR by reviewing the research objectives and contribution, provides a critique and a summary of my personal learning.

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APPENDICES

Appendix A Quality appraisal

N	Article	Q1	Q2	Q3	Q4	Q5	Overall
1	Ackermann, F. and Belton, V., 1994. Managing corporate knowledge experiences with SODA and V.I.S.A. *British Journal of Management*, 5(3), p.163.	3	3	3	3	3	15
2	Bell, P.C., 1985. Visual Interactive Modeling as an Operations Research Technique. *Interfaces*, 15(4), pp.26–33.	3	3	3	3	3	15
3	Biswas, S. and Narahari, Y., 2004. Object oriented modeling and decision support for supply chains. *European Journal of Operational Research*, 153(3), pp.704–726.	3	3	3	3	3	15
4	Browne, G.J., Curley, S.P. and Benson, P.G., 1997. Evoking information in probability assessment: Knowledge maps and reasoning-based directed questions. *Management Science*, 43(1), pp.1–14.	3	3	3	3	3	15
5	Burchill, G. and Fine, C.H., 1997. Time versus market orientation in product concept development: Empirically-based theory generation. *Management Science*, 43(4), pp.465–478.	3	3	3	3	3	15
6	Carravilla, M.A. and de Sousa, J.P., 1995. Hierarchical production planning in a make-to-order company: A case study. *European Journal of Operational Research*, 86(1), p.43.	3	2	2	3	2	12
7	Chau, P.Y.K. and Bell, P.C., 1995. Designing effective simulation-based decision support systems: An empirical assessment of three types of decision support systems. *The Journal of the Operational Research Society*, 46(3), p.315.	3	3	3	3	3	15
8	Čižman, A. et al., 2004. Improving competitiveness in veneers production by a simple-to-use DSS. *European Journal of Operational Research*, 156(1), pp.241–260.	3	3	3	3	3	15
9	Cortes, P. et al., 2001. Decision support system for planning telecommunication networks: A case study applied to the Andalusian region. *The Journal of the Operational Research Society*, 52(3), pp.283–290.	3	3	3	2	2	13
10	Cottyn, J. et al., 2011. A method to align a manufacturing execution system with Lean objectives. *International Journal of Production Research*, 49(14), pp.4397–4413.	2	2	2	2	2	10
11	Day, D.L., DeSarbo, W.S. and Oliva, T.A., 1987. Strategy Maps: A Spatial Representation of Intra-Industry Competitive Strategy. *Management Science*, 33(12), p.1534.	3	3	3	3	3	15
12	Dey, P.K., 2012. Project risk management using multiple criteria decision-making technique and decision tree analysis: a case study of Indian oil refinery. *Production Planning & Control*, 23(12), pp.903–921.	3	3	3	3	3	15
13	Ganaway, T.R.W. and W.A.W. and K.R.F. and L.B.W. and S.N., 2003. Bad numbers: coping with flawed decision support. *The Journal of the Operational Research Society*, 54(9), pp.949–957.	3	3	2	3	2	13
14	Grabowski, M. and Sanborn, S., 1992. Knowledge representation and reasoning in a real-time operational control system: The shipboard piloting expert system (SPES). *Decision Sciences*, 23(6), p.1277.	3	3	3	3	3	15
15	Hess, S.W., 1993. Swinging on the branch of a tree: Project selection applications. *Interfaces*, 23(6), p.5.	2	2	3	3	2	12
16	Hodgkin, J., Belton, V. and Koulouri, A., 2005. Supporting the intelligent MCDA user: A case study in multi-person multi-criteria decision support. *European Journal of Operational Research*, 160(1), pp.172–189.	3	3	3	3	3	15
17	Hu, W. et al., 2012. Corporate dashboards for integrated business and engineering decisions in oil refineries: An agent-based approach. *Decision Support Systems*, 52(3), p.729.	3	3	3	3	3	15
18	Hurrion, R.D., 1985. Implementation of a Visual Interactive Consensus Decision Support System. *European Journal of Operational Research*, 20(2), p.138.	2	3	2	2	2	11
19	Huysmans, J. et al., 2011. An empirical evaluation of the comprehensibility of decision table, tree and rule based predictive models. *Decision Support Systems*, 51(1), p.141.	3	3	3	3	3	15
20	Jam, H.K., Ramamurthy, K. and Sundaram, S., 2006. Effectiveness of Visual Interactive Modeling in the Context of Multiple-Criteria Group Decisions. *IEEE Transactions on Systems, Man & Cybernetics: Part A*, 36(2), pp.298–318.	3	2	3	3	3	14

21	Kayis, B. and Karningsih, P.D., 2012. SCRIS: A knowledge-based system tool for assisting manufacturing organizations in identifying supply chain risks. *Journal of Manufacturing Technology Management*, 23(7), pp.834–852.	2	2	2	2	2	10
22	Kirkpatrick, P. and Bell, P.C., 1989. Visual Interactive Modeling in Industry: Results from a Survey of Visual Interactive Model Builders. *Interfaces*, 19(5), pp.71–79.	3	2	2	2	2	11
23	Kumar, S. and Arbi, a. S., 2008. Outsourcing strategies for apparel manufacture: A case study. *Journal of Manufacturing Technology Management*, 19(1), pp.73–91.	2	2	2	2	2	10
24	Lembersky, M.R. and Chi, U.H., 1986. Weyerhaeuser Decision Simulator Improves Timber Profits. *Interfaces*, 16(1), p.6.	2	2	2	2	2	10
25	Levary, R.R. and Kalchik, S., 1984. A Visual Based Group Decision-Making Process for Layout Finalisation of Large Offices. *International Journal of Operations & Production Management*, 4(2), p.13.	3	3	2	2	2	12
26	Lu, T.-C. and Druzdzel, M.J., 2009. Interactive construction of graphical decision models based on causal mechanisms. *European Journal of Operational Research*, 199(3), p.873.	3	3	3	3	3	15
27	Maliapen, M. and Dangerfield, B.C., 2010. A system dynamics-based simulation study for managing clinical governance and pathways in a hospital. *The Journal of the Operational Research Society*, 61(2), pp.255–264.	2	2	2	2	2	10
28	Mangla, S., Madaan, J. and Chan, F.T.S., 2013. Analysis of flexible decision strategies for sustainability-focused green product recovery system. *International Journal of Production Research*, 51(11), pp.3428–3442.	2	2	2	2	2	10
29	Naruo, N., Lehto, M. and Salvendy, G., 1990. Development of a knowledge-based decision support system for diagnosing malfunctions of advanced production equipment. *International Journal of Production Research*, 28(12), p.2259.	3	3	3	3	2	14
30	New, S.J., Lockett, A.G. and Boaden, R.J., 1991. Using Simulation in Capacity Planning. *The Journal of the Operational Research Society*, 42(4), p.271.	3	3	3	3	3	15
31	Ozdamar, L. et al., 1998. A hierarchical decision support system for production planning (with case study). *European Journal of Operational Research*, 104(3), pp.403–422.	2	2	3	2	2	11
32	Pal, P. and Kumar, B., 2008. “16T”: toward a dynamic vendor evaluation model in integrated SCM processes. *Supply Chain Management*, 13(6), pp.391–397.	3	3	3	3	3	15
33	Persson, F., 2011. SCOR template—A simulation based dynamic supply chain analysis tool. *International Journal of Production Economics*, 131(1), pp.288–294.	2	2	2	2	2	10
34	Seret, A. et al., 2012. A new SOM-based method for profile generation: Theory and an application in direct marketing. *European Journal of Operational Research*, 220(1), p.199.	2	3	3	2	2	12
35	Siskos, Y., Spyridakos, A. and Yannacopoulos, D., 1999. Using artificial intelligence and visual techniques into preference disaggregation analysis: The MIIDAS system. *European Journal of Operational Research*, 113(2), pp.281–299.	3	3	3	3	3	15
36	Vessey, I., 1991. Cognitive Fit: A Theory-Based Analysis of the Graphs Versus. *Decision Sciences*, 22(2), p.219.	3	3	3	3	2	14
37	Völkner, P. and Werners, B., 2000. Decision support system for business process planning. *European Journal of Operational Research*, 125(3), pp.633–647.	2	2	2	2	2	10
38	Walker, J., 1994. Graphical analysis for machine replacement: A case study. *International Journal of Operations & Production Management*, 14(10), p.54.	3	3	3	3	2	14
39	Wu, J. et al., 2013. A matrix-based Bayesian approach for manufacturing resource allocation planning in supply chain management. *International Journal of Production Research*, 51(5), pp.1451–1463.	2	3	2	2	2	11
40	Wu, W.-W., Lan, L.W. and Lee, Y.-T., 2011. Exploring decisive factors affecting an organization’s SaaS adoption: A case study. *International Journal of Information Management*, 31(6), pp.556–563.	2	2	2	2	2	10
41	Zmud, R.W., 1978. An Empirical Investigation of the Dimensionality of the Concept of Information. *Decision Sciences*, 9(2), p.187.	3	2	2	2	2	11

Appendix B Data extraction

N	Article	Theoretical framework/ perspective	Managerial challenge / problem	Types of decisions in focus	Sample selection, size and characteristics	Type of analytics used	Practical implications (specially for decision in focus)
1	Ackermann, F. and Belton, V., 1994. Managing corporate knowledge experiences with SODA and V.I.S.A. *British Journal of Management*, 5(3), p.163.	Decision Theory	Plan: Group problem solving, decision making and strategy development in a variety of setting. Public and private sector across all levels and departments.	Plan, Strategic planning, Group-Strategy development	Managers from different levels in the organisation	Cognitive mapping for visual representation of problems	Conflicting points of view can be displayed revealing possible dilemmas, looks and undesirable ramifications. Representation of all of the views of the group, members are able to see their ideas alongside those of others in a non-threatening environment. The utilisation of the model helps to ensure that a more robust, better considered decision is made by the group. Its interactive nature and the ability to carry out analysis quickly, the group is able to explore, record, modify, analyse and display the knowledge in a variety of ways.
2	Bell, P.C., 1985. Visual Interactive Modeling as an Operations Research Technique. *Interfaces*, 15(4), pp.26–33.	System Theory	Deliver/Planning: Production planning, queuing systems analysis, personnel training, job shop scheduling, traffic flow analysis, assembly-line design.	Plan, Production/Delivery Planning, Production / Delivery Optimisation	Case based, Single case	Visual interactive modelling of two types "Representational graphic models" and "iconic graphic models"	Enable an alternative approach in OR when constructing pure OR models is challenging. Enable better marketing of OR to managers. Enhances trust in OR.
3	Biswas, S. and Narahari, Y., 2004. Object oriented modeling and decision support for supply chains. *European Journal of Operational Research*, 153(3), pp.704–726.	System Theory	Plan and Deliver: Optimisation of inventory	Plan, Inventory Management, Inventory Policy optimisation	Case based, Single Case	Object oriented modelling with a faithful representation of the SC	Representations enable a rapid and flexible decision-making in a cross-level (strategic, tactical, operational) approach - Different levels of abstraction
4	Browne, G.J., Curley, S.P. and Benson, P.G., 1997. Evoking information in probability assessment: Knowledge maps and reasoning-based directed questions. *Management Science*, 43(1), pp.1–14.	Decision Theory	Experiment: Decision-making in general	General, ,	Experiment,	Knowledge map methodology as a structuring tool to aid decision makers	Knowledge maps elicit higher quantity and quality of information from decision makers engaged in probability assessment task.

5	Burchill, G. and Fine, C.H., 1997. Time versus market orientation in product concept development: Empirically-based theory generation. *Management Science*, 43(4), pp.465–478.	Control Theory	Make: product concept development	Make, Manufacturing, Product development	Survey,	Methodology developed in the course of the papers called Inductive system diagram technique	Identification of key variables associated with the product concept development. Rigorous tool for systematically collect, organise, and distil large amounts of field-based data.
6	Carravilla, M.A. and de Sousa, J.P., 1995. Hierarchical production planning in a make-to-order company: A case study. *European Journal of Operational Research*, 86(1), p.43.	Control Theory	Plan: Production planning in a MTO company. Quoting due dates, production scheduling, plant layout decisions and line balancing issues	Plan, Production planning, Production Scheduling	Case based, Single Case	DSS for plant layout decisions and line balancing issues using a special interface designed to involve the various participants in the planning process	interface enables the involvement of various participants in the planning process. It became a highly valuable computer tool in production planning, layout design and assignment of orders
7	Chau, P.Y.K. and Bell, P.C., 1995. Designing effective simulation-based decision support systems: An empirical assessment of three types of decision support systems. *The Journal of the Operational Research Society*, 46(3), p.315.	System Theory	Experiment: Decision-making in general	General, ,	Experiment,	Visual Interactive Simulation - a combination of iconic-computer-generated animation and flexible user interaction.	Visual Interactive Simulations paired with traditional tools showed to be more effective at the decision-making process than the tools without VIS.
8	Čižman, A. et al., 2004. Improving competitiveness in veneers production by a simple-to-use DSS. *European Journal of Operational Research*, 156(1), pp.241–260.	Control Theory	Make and Deliver: Production of veneers improvement by cutting stock problem	Make, Inventory Management, Stock reduction	Case based, Single Case	Simple-to-use managerial DSS with a user-friendly graphical interface	For small and medium-size organisations simple-to-use DSS with a user-friendly graphical interface bring OR knowledge closer to its user. Supports the order processing more efficiently and helps to keep the inventory of finished goods ALAP. Visual interfaces empower front-line decision makers.
9	Cortes, P. et al., 2001. Decision support system for planning telecommunication networks: A case study applied to the Andalusian region. *The Journal of the Operational Research Society*, 52(3), pp.283–290.	Control Theory	Plan: Optimisation of network planning process	Plan, Resource Allocation, Supply network optimisation	Case based, Single Case	Simple-to-use managerial DSS for planning with a user-friendly graphical interface	Visual interface allows interactive analysis of different scenarios. This approach includes more information into decision process than is usually allowed. Ability to deal with less structured situations and the flexibility to evaluate alternative scenarios.
10	Cottyn, J. et al., 2011. A method to align a manufacturing execution system with Lean objectives. *International Journal of Production Research*, 49(14), pp.4397–4413.	Control Theory	Make: manufacturing alignment with lean objectives	Make, Performance Improvement, Manufacturing process and objectives alignment	Case based, Single Case	Mapping of manufacturing execution system (MES) to trigger, feed or validate the lean decision-making process by providing useful information.	Real-time production information is crucial to make important business decisions. Alignment of manufacturing execution systems with lean objectives. This brings valuable insights about the dependency between MES and Lean activities

11	Day, D.L., DeSarbo, W.S. and Oliva, T.A., 1987. Strategy Maps: A Spatial Representation of Intra-Industry Competitive Strategy. *Management Science*, 33(12), p.1534.	Decision Theory	Plan: Strategic business decisions for competitive analysis	Plan, Strategic planning, Competitive analysis	Case based, Single Case	Business level strategy maps using multi-dimensional scaling	Mapping of complex relations among competitive strategy variables and performance simultaneously. The methodology captures the simultaneous, multidimensional, and interrelated nature of business strategy and performance for a group of business whiten an industry. Descriptive tool in competitive strategy
12	Dey, P.K., 2012. Project risk management using multiple criteria decision-making technique and decision tree analysis: a case study of Indian oil refinery. *Production Planning & Control*, 23(12), pp.903–921.	Decision Theory	Make: construction project risk management - Risk response development and risk mitigation strategy	Make, Risk Management, Risk Mitigation strategy	Case based, Single Case	Cause and effect diagrams and decision trees - Risk mapping, DTA, AHP	Optimises the selection of risk mitigating strategy.
13	Ganaway, T.R.W. and W.A.W. and K.R.F. and L.B.W. and S.N., 2003. Bad numbers: coping with flawed decision support. *The Journal of the Operational Research Society*, 54(9), pp.949–957.	Decision Theory	Make and Decision-making in general:	General, ,	Case based, Single Case	Use of visual support in form of graphical representations to guide decision using the human ability to overcome flawed decision support	Poor interface design can play in the use or misuse of DSS.
14	Grabowski, M. and Sanborn, S., 1992. Knowledge representation and reasoning in a real-time operational control system: The shipboard piloting expert system (SPES). *Decision Sciences*, 23(6), p.1277.	Control Theory	Make: Shipboard piloting	Make, Piloting, Real-time Shipboard piloting	Case based, Single Case	Knowledge representation and reasoning system for shipboard piloting system - User interface	Visual analytics reduce information overload enabling better ship handling. Integrating data from several navigational instruments into a single workstation free the watch officers time and attention so that more attention can be focused on safe and efficient navigation.
15	Hess, S.W., 1993. Swinging on the branch of a tree: Project selection applications. *Interfaces*, 23(6), p.5.	Decision Theory	Make: R&D project selection	Make, Project selection, Group Project Selection	Case based, Single Case	Visual sensitivity analysis in decision trees to screen new product ideas and decide on a major effort in new process research.	Visual sensitivity analysis gave management confidence in the model conclusions. Visual representations using logical and simple models overcome data scarcity. Provide better basis for selecting projects than intuition, a check list or the power of personality.

16	Hodgkin, J., Belton, V. and Koulouri, A., 2005. Supporting the intelligent MCDA user: A case study in multi-person multi-criteria decision support. *European Journal of Operational Research*, 160(1), pp.172–189.	System Theory	Plan: quick planning under stress and time-pressure DSS for multi-user, multi-criteria evaluations	Plan, Performance Improvement, Process planning	Case based, Single Case	Visual interactive modelling. PCA plots, Triangle Plots,	Enables the user to quickly make sense of complex multiuser, multi-criteria evaluations in stressful and time pressured environment. Visual displays act as a catalyst for thinking, a sounding board against which intuition can be tested and, a vehicle for learning. Page 175 Ability to quickly interpret a large volume of data and decide on appropriate analysis to conduct, without overlooking important issues.
17	Hu, W. et al., 2012. Corporate dashboards for integrated business and engineering decisions in oil refineries: An agent-based approach. *Decision Support Systems*, 52(3), p.729.	System Theory	Make: integrated business and engineering decisions in oil refineries	Make, Performance Improvement, Business and Engineering alignment	Case based, Single Case	Corporate dashboards for integrated business engineering decisions using an agent based approach. Flow diagrams, Dashboards, Mapping, modelling, Agent based simulation.	Enable management to make integrated decisions.
18	Hurrion, R.D., 1985. Implementation of a Visual Interactive Consensus Decision Support System. *European Journal of Operational Research*, 20(2), p.138.	System Theory	Plan, Make and Deliver: Production and distribution planning models for interactive planning sessions.	Plan, Production/Delivery Planning, Production / Delivery Optimisation	Case based, Single Case	Visual interactive consensus decision support system based on simulation	The interaction between DSS and the user by means of an interface enhances the manager's trust and consequently better specifications and closer to optimum decisions.
19	Huysmans, J. et al., 2011. An empirical evaluation of the comprehensibility of decision table, tree and rule based predictive models. *Decision Support Systems*, 51(1), p.141.	Decision Theory	Experiment: Decision-making in general	General, ,	Experiment,	Knowledge representation using decision tables, trees and rule-based predictive models to support decision making processes	Decision tables perform better than binary decision tress, or propositional rules or oblique rules.
20	Jam, H.K., Ramamurthy, K. and Sundaram, S., 2006. Effectiveness of Visual Interactive Modelling in the Context of Multiple-Criteria Group Decisions. *IEEE Transactions on Systems, Man & Cybernetics: Part A*, 36(2), pp.298–318.	Decision Theory	Experiment: Multi-criteria decision-making, group decision-making, Decision-making in general	General, ,	Experiment,	Visual interactive modelling to present information on decision processes	Visualisation technologies can aid in the assimilation of complex qualitative and quantitative information by the decision maker and allow the abstraction of vast information space. Quicker decisions. Better consensus. The quality of the decision that is made by the groups using visual interaction modelling is not better than those without this support.

21	Kayis, B. and Karningsih, P.D., 2012. SCRIS: A knowledge-based system tool for assisting manufacturing organizations in identifying supply chain risks. *Journal of Manufacturing Technology Management*, 23(7), pp.834–852.	Decision Theory	Source and Make: Risk management - Risk identification - Choosing different process strategies (between MTS, MTO and ETO)	Source, Risk Management, Source and make strategy Selection	Case based, Multiple Case	user interface based on Knowledge Base Systems - Mapping the interactions	Promotes communication and collaboration between SC partners and is positive in SC risk management.
22	Kirkpatrick, P. and Bell, P.C., 1989. Visual Interactive Modeling in Industry: Results from a Survey of Visual Interactive Model Builders. *Interfaces*, 19(5), pp.71–79.	System Theory	Survey: Decision-making in general	General, ,	Survey,	Visual Interactive Modelling	Real-time graphic display of model output into systems aid solving decision problems. Visual Interactive Modelling provides major benefits to managers in the area of model validation, incorporation or qualitative dimensions into modelling, and modelling complex systems. VMI make management becoming more involved in model building and use. Improves managerial understanding of the decision optimism. Better interaction with the decision maker, more useful and easier to understand models and better decisions.
23	Kumar, S. and Arbi, a. S., 2008. Outsourcing strategies for apparel manufacture: A case study. *Journal of Manufacturing Technology Management*, 19(1), pp.73–91.	Control Theory	Plan: outsourcing strategies	Plan, Performance Improvement, Outsourcing	Case based, Single Case	Process Mapping	The process modelling of the SC is a useful decision analysis tool. Improved IT and logistics capabilities can minimize the variability recognized in major components of customer lead-time: ocean freight transportation time, order processing time and manufacturing time.
24	Lembersky, M.R. and Chi, U.H., 1986. Weyerhaeuser Decision Simulator Improves Timber Profits. *Interfaces*, 16(1), p.6.	System Theory	Make: Raw-materials returns management and product manufacturing	Make, Performance Improvement, Resource recovery	Case based, Single Case	Visual simulation - Video Interactive stem Inspection and Optimization	The VISION implementation led to profit increase, change of mentality of doing business, better service. Enabled top management involvement in funding, testing and implementation. Enabled the use of the DSS without specialist OR background knowledge. Same principles were applied to other management problems such as truck-routings and facility design. Change in corporate behaviour.
25	Levary, R.R. and Kalchik, S., 1984. A Visual Based Group Decision-Making Process for Layout Finalisation of Large Offices. *International Journal of Operations & Production Management*, 4(2), p.13.	Decision Theory	Plan and Make: Group decision-making process for layouting	Plan, Layouts, Group layout definition	Case based, Single case	Visual-based group decision-making process for layout - Architectural drawings of alternative layouts	Visual based group decision-making process based on the analysis, modification and re-design enabled an effective layout, which can increase employee morale and productivity.

26	Lu, T.-C. and Druzdzel, M.J., 2009. Interactive construction of graphical decision models based on causal mechanisms. *European Journal of Operational Research*, 199(3), p.873.	Decision Theory	Experiment: Decision-making in general	General, ,	40 Graduate students	Graphical Decision Model based on casual mechanism	Graphical displays representing under-constrained systems help model builders to explore relevant mechanisms and specifying exogenous variables.
27	Maliapen, M. and Dangerfield, B.C., 2010. A system dynamics-based simulation study for managing clinical governance and pathways in a hospital. *The Journal of the Operational Research Society*, 61(2), pp.255–264.	Control Theory	Deliver and Plan: Clinical governance and pathways in a hospital	Plan, Performance Improvement, Process Planning	Case based, Single Case	DSS with an interactive visual interface to test scenarios	The use of visual interfaces enable executives to manipulate the DSS to test various scenarios. The developed DSS with interface showed substantial reduction in length of stay, costs and resource utilisation after the case study.
28	Mangla, S., Madaan, J. and Chan, F.T.S., 2013. Analysis of flexible decision strategies for sustainability-focused green product recovery system. *International Journal of Production Research*, 51(11), pp.3428–3442.	System Theory	Return: Decisions on resource recovery and performance improvement	Return, Performance Improvement, Resource recovery	Case based, Single Case	Interpretative structural modelling (ISM) - graphical categorisation of the variables is done on the basis of the impact on performance	Visual representations enable a better interpretation of the interrelationships among the associated variables. Overall better processing times, environmental benefits, capacity utilisation, etc.
29	Naruo, N., Lehto, M. and Salvendy, G., 1990. Development of a knowledge-based decision support system for diagnosing malfunctions of advanced production equipment. *International Journal of Production Research*, 28(12), p.2259.	Control Theory	Make: Diagnosing malfunctions of advanced production equipment	Make, Equipment maintenance, Diagnosing malfunctions	Case based, Single Case	Flow diagrams transformed into a large logic network diagram	92% of the malfunctions were successfully diagnosed by the DSS based on a large logic network diagram.
30	New, S.J., Lockett, A.G. and Boaden, R.J., 1991. Using Simulation in Capacity Planning. *The Journal of the Operational Research Society*, 42(4), p.271.	System Theory	Plan: manufacturing capacity planning	Plan, Production Planning, Manufacturing Capacity Planning	Case based, Single Case	Visual interactive modelling	Visual Interactive modelling provides OR with better communication between client and analyst, easier validation of the model, better debugging of model code, evaluation of alternative policies by users. Negatively it might undermine the statistical validity of simulation results and misinterpretation of visual outputs.
31	Ozdamar, L. et al., 1998. A hierarchical decision support system for production planning (with case study). *European Journal of Operational Research*, 104(3), pp.403–422.	Control Theory	Plan: Production planning	Plan, Production Planning, Production Scheduling	Case based, Single Case	Interactive User interface	Interactive user interface eases data manipulation and highly interactive system at all planning levels.

32	Pal, P. and Kumar, B., 2008. "16T": toward a dynamic vendor evaluation model in integrated SCM processes. *Supply Chain Management*, 13(6), pp.391–397.	Control Theory	Source: Vendor evaluation and selection	Source, Supplier management, Vendor Evaluation and Selection	Case based, Single Case	Dashboard data for decisions regarding evaluation of vendors	The DSS with the dashboard made the task quick and easy, more practical making the existing algorithms more adaptable.
33	Persson, F., 2011. SCOR template—A simulation based dynamic supply chain analysis tool. *International Journal of Production Economics*, 131(1), pp.288–294.	Control Theory	Plan: SC design and value-stream mapping	Plan, Performance Improvement, SC (re)design	Case based, Single Case	Simulation used to map the SC (value stream mapping)	Enabled the identification of bottle-necks. Enabled the comparison of different scenarios in production networks for one specific product.
34	Seret, A. et al., 2012. A new SOM-based method for profile generation: Theory and an application in direct marketing. *European Journal of Operational Research*, 220(1), p.199.	Network Theory	Deliver: Direct marketing profile generation and individual targeting.	Deliver, Marketing, Direct Marketing	Case based, Single Case	Visual exploration facility enabled by SOM and clustering techniques to extract salient dimensions for direct marketing and generate profiles.	The developed generic method for profile generation can be applied to all cases where the SOM technology is used. The method enables to formalise intuitive feelings and insights resulting from the combination of a SOM analysis and the extraction of silent dimensions. The visualisation power reinforces the segmentation task.
35	Siskos, Y., Spyridakos, A. and Yannacopoulos, D., 1999. Using artificial intelligence and visual techniques into preference disaggregation analysis: The MIIDAS system. *European Journal of Operational Research*, 113(2), pp.281–299.	Control Theory	Decision-making in general	General, ,	Case based, Single Case	using AI and visual techniques for preference disaggregation and graphic interface	The set of visual techniques create the interface between the user and the AI methods. Visual techniques provide feedback to the user.
36	Vessey, I., 1991. Cognitive Fit: A Theory-Based Analysis of the Graphs Versus. *Decision Sciences*, 22(2), p.219.	Decision Theory	Decision-making in general	General, ,	Literature Survey,	Graphical vs. tabular representations for decision-making process	Graphical and tabular representations present the same information in different ways. Graphical representations emphasize spatial information while tables the symbolic information. Tasks can be divided into two types: spatial and symbolic. Performance on a task will be enhanced when there is a cognitive fit between the information emphasized by the representation type and the required by the task type. Visual representations provide the link between the problem solver and the process. They lead to quicker and more accurate problem solving.

37	Völkner, P. and Werners, B., 2000. Decision support system for business process planning. *European Journal of Operational Research*, 125(3), pp.633–647.	Control Theory	Plan: Business process planning, optimisation of business processes,	Plan, Performance Improvement, Process Optimisation	Case based, Single Case	Pictorial representation of SC using generic objects	Pictorial representation assist in analysing the static structure of the process and a simulation system for quantitative evaluation of the dynamic behaviour
38	Walker, J., 1994. Graphical analysis for machine replacement: A case study. *International Journal of Operations & Production Management*, 14(10), p.54.	Control Theory	Make: Decidions on machine replacement	Make, Equipment maintenance, Machine replacement	Case based, Single Case	Graphical analysis based on a plot for machine replacement	The use of graphical analysis overcomes the poor quality data. It is quick and simple. What if analysis using a simple "at a glance" plots displays the allowable changes in the parameter values for which the economic life remains optimal.
39	Wu, J. et al., 2013. A matrix-based Bayesian approach for manufacturing resource allocation planning in supply chain management. *International Journal of Production Research*, 51(5), pp.1451–1463.	Decision Theory	Plan: Manufacturing resource allocation planning	General, ,	Case based, Single Case	Network-based resource allocation planning using a Bayesian approach - matrix-based representations	Matrix-based representation of the resource allocation plan provides supply chain modelling with a good basis to understand problem complexity, support computer reasoning, facilitate resource re-allocation, and add quantitative information.
40	Wu, W.-W., Lan, L.W. and Lee, Y.-T., 2011. Exploring decisive factors affecting an organization's SaaS adoption: A case study. *International Journal of Information Management*, 31(6), pp.556–563.	Network Theory	Decision-making in general	Plan, Resource allocation, Manufacturing Resource Allocation	Case based, Single Case	Cause-effect diagrams	The company concern is more about strategic-oriented benefits than economic oriented benefits. The cause-effect diagram based on perceived benefits and perceived risks which are helpful to perform better decision-makings and to initiate more effective marketing strategies. It provides a paradigm for other organisations to systematically look into complex factors while planning to introduce the DSS solutions.
41	Zmud, R.W., 1978. An Empirical Investigation of the Dimensionality of the Concept of Information. *Decision Sciences*, 9(2), p.187.	Decision Theory	Decision-making in general	General, ,	Experiment,	graphical formats vs. tabular formats vs. bar-charts	A graphical format is preferred over tabular formats and over bar chart formats.

Appendix C Article source and country of origin of the first author

N	Article	Origin or the first author	EBSCO	PROQUEST	SCOPUS	Exception
1	Ackermann, F. and Belton, V., 1994. Managing corporate knowledge experiences with SODA and V.I.S.A. *British Journal of Management*, 5(3), p.163.	UK	1	1		
2	Bell, P.C., 1985. Visual Interactive Modeling as an Operations Research Technique. *Interfaces*, 15(4), pp.26–33.	Canada				1
3	Biswas, S. and Narahari, Y., 2004. Object oriented modeling and decision support for supply chains. *European Journal of Operational Research*, 153(3), pp.704–726.	India	1	1		
4	Browne, G.J., Curley, S.P. and Benson, P.G., 1997. Evoking information in probability assessment: Knowledge maps and reasoning-based directed questions. *Management Science*, 43(1), pp.1–14.	USA		1		
5	Burchill, G. and Fine, C.H., 1997. Time versus market orientation in product concept development: Empirically-based theory generation. *Management Science*, 43(4), pp.465–478.	UK	1	1	1	
6	Carravilla, M.A. and de Sousa, J.P., 1995. Hierarchical production planning in a make-to-order company: A case study. *European Journal of Operational Research*, 86(1), p.43.	Portugal		1		
7	Chau, P.Y.K. and Bell, P.C., 1995. Designing effective simulation-based decision support systems: An empirical assessment of three types of decision support systems. *The Journal of the Operational Research Society*, 46(3), p.315.	Canada		1		
8	Čižman, A. et al., 2004. Improving competitiveness in veneers production by a simple-to-use DSS. *European Journal of Operational Research*, 156(1), pp.241–260.	Slovenia	1	1		
9	Cortes, P. et al., 2001. Decision support system for planning telecommunication networks: A case study applied to the Andalusian region. *The Journal of the Operational Research Society*, 52(3), pp.283–290.	Spain		1		
10	Cottyn, J. et al., 2011. A method to align a manufacturing execution system with Lean objectives. *International Journal of Production Research*, 49(14), pp.4397–4413.	Belgium	1			
11	Day, D.L., DeSarbo, W.S. and Oliva, T.A., 1987. Strategy Maps: A Spatial Representation of Intra-Industry Competitive Strategy. *Management Science*, 33(12), p.1534.	USA		1		
12	Dey, P.K., 2012. Project risk management using multiple criteria decision-making technique and decision tree analysis: a case study of Indian oil refinery. *Production Planning & Control*, 23(12), pp.903–921.	UK	1			
13	Ganaway, T.R.W. and W.A.W. and K.R.F. and L.B.W. and S.N., 2003. Bad numbers: coping with flawed decision support. *The Journal of the Operational Research Society*, 54(9), pp.949–957.	USA		1		
14	Grabowski, M. and Sanborn, S., 1992. Knowledge representation and reasoning in a real-time operational control system: The shipboard piloting expert system (SPES). *Decision Sciences*, 23(6), p.1277.	USA		1		
15	Hess, S.W., 1993. Swinging on the branch of a tree: Project selection applications. *Interfaces*, 23(6), p.5.	USA		1		
16	Hodgkin, J., Belton, V. and Koulouri, A., 2005. Supporting the intelligent MCDA user: A case study in multi-person multi-criteria decision support. *European Journal of Operational Research*, 160(1), pp.172–189.	UK	1	1		
17	Hu, W. et al., 2012. Corporate dashboards for integrated business and engineering decisions in oil refineries: An agent-based approach. *Decision Support Systems*, 52(3), p.729.	USA		1		
18	Hurrion, R.D., 1985. Implementation of a Visual Interactive Consensus Decision Support System. *European Journal of Operational Research*, 20(2), p.138.	UK		1		
19	Huysmans, J. et al., 2011. An empirical evaluation of the comprehensibility of decision table, tree and rule based predictive models. *Decision Support Systems*, 51(1), p.141.	Belgium		1		

20	Jam, H.K., Ramamurthy, K. and Sundaram, S., 2006. Effectiveness of Visual Interactive Modeling in the Context of Multiple-Criteria Group Decisions. *IEEE Transactions on Systems, Man & Cybernetics: Part A*, 36(2), pp.298–318.	USA				1
21	Kayis, B. and Karningsih, P.D., 2012. SCRIS: A knowledge-based system tool for assisting manufacturing organizations in identifying supply chain risks. *Journal of Manufacturing Technology Management*, 23(7), pp.834–852.	Australia	1	1	1	
22	Kirkpatrick, P. and Bell, P.C., 1989. Visual Interactive Modeling in Industry: Results from a Survey of Visual Interactive Model Builders. *Interfaces*, 19(5), pp.71–79.	Canada				1
23	Kumar, S. and Arbi, a. S., 2008. Outsourcing strategies for apparel manufacture: A case study. *Journal of Manufacturing Technology Management*, 19(1), pp.73–91.	USA			1	
24	Lembersky, M.R. and Chi, U.H., 1986. Weyerhaeuser Decision Simulator Improves Timber Profits. *Interfaces*, 16(1), p.6.	USA		1		
25	Levary, R.R. and Kalchik, S., 1984. A Visual Based Group Decision-Making Process for Layout Finalisation of Large Offices. *International Journal of Operations & Production Management*, 4(2), p.13.	USA	1	1		
26	Lu, T.-C. and Druzdzel, M.J., 2009. Interactive construction of graphical decision models based on causal mechanisms. *European Journal of Operational Research*, 199(3), p.873.	USA		1		
27	Maliapen, M. and Dangerfield, B.C., 2010. A system dynamics-based simulation study for managing clinical governance and pathways in a hospital. *The Journal of the Operational Research Society*, 61(2), pp.255–264.	UK		1		
28	Mangla, S., Madaan, J. and Chan, F.T.S., 2013. Analysis of flexible decision strategies for sustainability-focused green product recovery system. *International Journal of Production Research*, 51(11), pp.3428–3442.	India	1			
29	Naruo, N., Lehto, M. and Salvendy, G., 1990. Development of a knowledge-based decision support system for diagnosing malfunctions of advanced production equipment. *International Journal of Production Research*, 28(12), p.2259.	Japan	1			
30	New, S.J., Lockett, A.G. and Boaden, R.J., 1991. Using Simulation in Capacity Planning. *The Journal of the Operational Research Society*, 42(4), p.271.	UK		1		
31	Ozdamar, L. et al., 1998. A hierarchical decision support system for production planning (with case study). *European Journal of Operational Research*, 104(3), pp.403–422.	Turkey	1	1	1	
32	Pal, P. and Kumar, B., 2008. “16T”: toward a dynamic vendor evaluation model in integrated SCM processes. *Supply Chain Management*, 13(6), pp.391–397.	India		1		
33	Persson, F., 2011. SCOR template—A simulation based dynamic supply chain analysis tool. *International Journal of Production Economics*, 131(1), pp.288–294.	Sweden	1			
34	Seret, A. et al., 2012. A new SOM-based method for profile generation: Theory and an application in direct marketing. *European Journal of Operational Research*, 220(1), p.199.	Belgium		1		
35	Siskos, Y., Spyridakos, A. and Yannacopoulos, D., 1999. Using artificial intelligence and visual techniques into preference disaggregation analysis: The MIIDAS system. *European Journal of Operational Research*, 113(2), pp.281–299.	Greece	1	1		
36	Vessey, I., 1991. Cognitive Fit: A Theory-Based Analysis of the Graphs Versus. *Decision Sciences*, 22(2), p.219.	USA		1		
37	Völkner, P. and Werners, B., 2000. Decision support system for business process planning. *European Journal of Operational Research*, 125(3), pp.633–647.	Germany			1	
38	Walker, J., 1994. Graphical analysis for machine replacement: A case study. *International Journal of Operations & Production Management*, 14(10), p.54.	Singapore		1		
39	Wu, J. et al., 2013. A matrix-based Bayesian approach for manufacturing resource allocation planning in supply chain management. *International Journal of Production Research*, 51(5), pp.1451–1463.	China	1	1	1	
40	Wu, W.-W., Lan, L.W. and Lee, Y.-T., 2011. Exploring decisive factors affecting an organization’s SaaS adoption: A case study. *International Journal of Information Management*, 31(6), pp.556–563.	Taiwan	1			
41	Zmud, R.W., 1978. An Empirical Investigation of the Dimensionality of the Concept of Information. *Decision Sciences*, 9(2), p.187.	USA		1		

Appendix D Types of decisions vs. types of visual analytics

			Diagram					Graphics		GUI	Mapping								Modelling				Simulation	Statistics	
			Cause and effect diagrams	Decision tables	Decision Trees	Flow diagrams	Inductive System Diagram Technique	Graphics	Triangle Plots	User interface	Cognitive Mapping	Knowledge Mapping	Layout Mapping	Mapping	Process Mapping	Risk Mapping	Strategy Mapping	Value Stream Mapping	Interpretative Structural Modelling	Object Oriented Modelling	Probabylistic graphical model	Visual Interactive Modelling	Agent Based simulation	PCA	SOM & Clustering
Non Specific			Wu et al. (2011),	Huysmans et al. (2011),	Huysmans et al. (2011),			Zmud (1978), Vessey (1991), Ganaway et al. (2003), Lu and Druzdzel (2009),		Siskos et al. (1999),		Browne et al. (1997),										Kirkpatrick and Bell (1989), Chau and Bell (1995), Jam et al. (2006),			
Source	Risk Management	Source and make strategy Selection												Kayis and Karningsih (2012),											
Source	Supplier management	Vendor Evaluation and Selection								Pal and Kumar (2008),															
Make	Equipment maintenance	Diagnosing malfunctions				Naruo et al. (1990),																			
Make	Equipment maintenance	Machine replacement						Walker (1994),																	
Make	Inventory Management	Stock reduction								Čižman et al. (2004),															
Make	Layouts	Group layout definition						Levary and Kalchik (1984),					Levary and Kalchik (1984),												
Make	Manufacturing	Product development					Burchill and Fine (1997),																		
Make	Performance Improvement	Business and Engineering alignement				Hu et al. (2012),				Hu et al. (2012),				Hu et al. (2012),									Hu et al. (2012),		
Make	Performance Improvement	Manufacturing process and objectives alignement												Cottyn et al. (2011),											
Make	Performance Improvement	Resource recovery																				Lembersky and Chi (1986),			
Make	Piloting	Real-time Shipboard pilloting								Grabowski and Sanborn (1992),		Grabowski and Sanborn (1992),													
Make	Production /Delivery Planning	Production / Delivery Optimisation																				Hurrion (1985),			
Make	Project selection	Group Project Selection			Hess (1993),																				
Make	Risk Management	Risk Mitigation strategy	Dey (2012),		Dey (2012),											Dey (2012),									
Make	Risk Management	Source and make strategy Selection												Kayis and Karningsih (2012),											
Deliver	Inventory Management	Inventory Policy optimisation																		Biswas and Narahari (2004),					
Deliver	Inventory Management	Stock reduction								Čižman et al. (2004),															
Deliver	Marketing	Direct Marketing																							Seret et al. (2012),
Deliver	Performance Improvement	Process Planning								Maliapen and Dangerfield (2010),															

	Production /Delivery Planning	Production / Delivery Optimisation																						
Return	Performance Improvement	Resource recovery																Mangla et al. (2013),			Lembersky and Chi (1986),			
	Inventory Management	Inventory Policy optimisation																	Biswas and Narahari (2004),					
	Layouts	Group layout definition						Levary and Kalchik (1984),					Levary and Kalchik (1984),											
	Performance Improvement	Outsourcing													Kumar and Arbi (2008),									
		Process Optimisation													Völkner and Werners (2000),							Bell (1985), Hurrion (1985),			
Plan		Process Planning							Hodgkin et al. (2005),	Maliapen and Dangerfield (2010),												Hodgkin et al. (2005),		Hodgkin et al. (2005),	
		SC (re)design																Persson (2011),							
	Production Planning	Manufacturing Capacity Planning																				New (1991),			
	Production /Delivery Planning	Production / Delivery Optimisation																				Bell (1985), Hurrion (1985),			
	Resource allocation	Manufacturing Resource Allocation																			Wu et al. (2013),				
		Supply network optimisation								Cortes et al. (2001),															
	Strategic planning	Competitive analysis															Day et al. (1987),								
		Group-Strategy development									Ackermann and Belton (1994),														
			2	1	3	2	1	7	1	9	1	2	2	4	2	1	1	1	1	2	1	12	1	1	1

Appendix E References against type of visual analytics

Type of visual analytics / Reference	Cause and effect diagrams	Decision tables	Decision Trees	Flow diagrams	Inductive System Diagram Technique	Graphics	Triangle Plots	User interface	Cognitive Mapping	Knowledge Mapping	Layout Mapping	Mapping	Process Mapping	Risk Mapping	Strategy Mapping	Value Stream Mapping	Interpretative Structural Modelling	Object Oriented Modelling	Probabylistic graphical model	Visual Interactive Modelling	PCA	Agent Based simulation	SOM & Clustering	Grand Total
Zmud (1978)	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Levary and Kalchik (1984)	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2
Bell (1985)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Hurrion (1985)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Lembersky and Chi (1986)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Day et al. (1987)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
Kirkpatrick and Bell (1989)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Naruo et al. (1990)	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
New (1991)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Vessey (1991)	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Grabowski and Sanborn (1992)	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Hess (1993)	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Ackermann and Belton (1994)	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Walker (1994)	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Carravilla and de Sousa (1995)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Chau and Bell (1995)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Browne et al. (1997)	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Burchill and Fine (1997)	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Ozdamar et al. (1998)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Siskos et al. (1999)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Völkner and Werners (2000)	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
Cortes et al. (2001)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Ganaway et al. (2003)	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Biswas and Narahari (2004)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
Čižman et al. (2004)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Hodgkin et al. (2005)	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	3
Jam et al. (2006)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
Kumar and Arbi (2008)	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
Pal and Kumar (2008)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Lu and Druzdzel (2009)	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Maliapen and Dangerfield (2010)	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Cottyn et al. (2011)	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
Huysmans et al. (2011)	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Persson (2011)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
Wu et al. (2011)	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Dey (2012)	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	3
Hu et al. (2012)	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	4
Kayis and Karningsih (2012)	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
Seret et al. (2012)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Mangla et al. (2013)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
Wu et al. (2013)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
Grand Total	2	1	3	2	1	6	1	9	1	2	1	3	2	1	1	1	1	1	1	8	1	1	1	51